A Study on the Factors Affecting the Auto Indices of the Indian Stock Markets – An ARDL Cointegration Approach

دراسة عن العوامل المؤثرة على مؤشرات قطاع الاليات (السيارات) في الأسواق المالية الهندية – منهجية الانحدار الذاتي للفجوات الزمنية (ARDL)

by

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ABSTRACT

The aim of this study is to analyze the relationship between selected macroeconomic variables and auto indices of the two major Indian stock markets (viz. Bombay Stock Exchange and National Stock Exchange) using monthly data during the time period, January 2017 to August 2019. Unit root test is performed to confirm the order of integration of the data. Bounds test reveals that there is a co-integrating relationship between the dependent and explanatory variables under both models of the study. Hence, autoregressive distributed lag (ARDL) model is employed to examine the co-integrating relationship between them. The results show that, exchange rate is a strong and statistically significant predictor of both S&P BSE auto index and Nifty auto index in the long run. The findings also reveal that, crude price, index of industrial production and repo rates are statistically significant determinants of Nifty auto index in the long run. In addition, first lag of crude price was seen to be a potential indicator of both the indices in the short-run. However, it was quite interesting to note the difference in the direction of relationship of crude price with the indices. The study provides some important policy implications.

ملخص

تهدف هذه الدراسة إلى تحليل الترابط بين بعض متغيرات الاقتصاد الكلي ومؤشرات قطاع الاليات (السيارات) في الأسواق المالية الهندية الرئيسية وهما بورصة بومباي والبورصة الوطنية، باستخدام البيانات الشهرية خلال الفترة الزمنية من يناير 2017 إلى أغسطس 2019.

وتمت هذه الدراسة من خلال إجراء اختبار جذور الوحدة للسلاسل الزمنية لمعرفة استقراريتها وتحديد درجة تكاملها. كشف إختبار الحدود أن هناك علاقة تكاملية بين المتغيرات التابعة والتفسيرية في نموذجي الدراسة. تم استخدام نموذج التأخير الموزع على الإنحدار الذاتي لتحليل علاقة التكامل المشترك بينهما. أظهرت النتائج ان سعر الصرف له علاقة قوية وذات دلالة إحصائية مع كلا مؤشرين السيارات في بوصة بومباي والبورصة الوطنية على المدى الطويل.

كما أظهرت النتائج ان بعض متغيرات الاقتصاد الكلي مثل أسعار النفط الخام ومؤشر الإنتاج الصناعي ومعدلات إعادة الشراء هي أيضا من العوامل المؤثرة على المدى الطويل في مؤشر السيارات في بورصة بومباي. علاوة على ذلك، كان ينظر إلى التأخير الأول في سعر النفط الخام كعامل مؤثر محتمل على المدى القصير في كل من مؤشر بورصة بومباي ومؤشر البورصة الوطنية للسيارات. من المثير للإهتمام ملاحظة الإختلاف في إتجاه علاقة سعرالنفط الخام مع مؤشرات كلا السوقين. من الجدير بالذكر ان الدراسة قدمت بعض التوصيات المهمة لصانعي القرار والمستثمرين.

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CHAPTER 1: INTRODUCTION

The decline in the Indian Automotive sector has been in the news since quite some time. An increase in the oil price could be a major factor for this downturn as per market analysts. But, government' recent changes in the fiscal policies, variation in other macroeconomic variables and changing consumer attitudes were also cited as the reasons for this downfall. Indian economy saw the biggest slump in the auto industry since July 2018 recording 30.9% decline in vehicles sales as of August 2019 (Hindustan Times 2019). This is recorded as the sharpest fall in automobile sales since December 2000. Various sources report that it is impacting the local economy as a whole. Apart from the direct effects of the auto sector on the Indian economy, many researchers contend that it has spillover effect in the economy as a number of industries are affected by it one way or the other (Shahabuddin 2009).

Bary & Andrew (2000, p.26) also describes a similar situation in the US betwixt an economic slowdown when the leading players in the sector fell from favor on Wall Street and were trading at half their 52-week highs. However, the Indian economy is growing at more than 7% at the moment and it seems somehow the auto industry is worst hit with the sectorial indices in both NSE and BSE hitting a low (Goyal 2019).

At present there are two indices viz Nifty Auto Index and S&P BSE Auto Index comprising 15 stocks each tracking the movement in the automobile industry in the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) respectively. Given the current scenario in the economic as well as the capital market in India, this study makes use of ARDL co-integration technique to analyze a possible link between identified macroeconomic variables and the auto indices of the Bombay Stock Exchange and the National Stock Exchange of India.

1.1 Significance & Motivation of Study

The significance and role of stock markets in achieving economic growth is critical because, stock markets being the center of a network of transactions is influenced by a number of economic factors (Ranjani & Dharmadasa 2018; Mohi-u-Din & Mubasher 2013). The aggregate performance of the auto industry in India can be seen from its indices that represent the movement of stock prices of the various listed companies being traded in the capital market. During the last one year both the S&P BSE Auto & Nifty Auto indices have lost more than 20% of their value. During the same time, the S&P BSE Sensex as well as the NIFTY 50 broad based indices have both grown by over 4%. Some newspaper sources reported that the downfall of the auto indices have coincided with a period of slowing GDP growth & decreasing interest rates in India.

The above discussions indicate that quite a lot of changes are happening in the Indian automobile industry which is having an impact on the enterprise as a whole and consequently in the performance of the auto stocks in the stock markets. A buoyant automotive sector is considered as an important indicator of the economic performance of any country (Shahabuddin 2009; Yadav, Sushil & Sagar 2015; Tambade, Singh & Modgil 2019). Many researchers have attempted to understand the relationship between macro economy and the stock market developments in general (Mishra et al. 2010; Kumar 2013; Tripathi & Seth 2014; Bhatia 2018). Yet, there is only limited discussion in literature regarding the impact of the macroeconomic factors on the movements of the auto indices in an Indian context. Hence this research study becomes relevant. The main aim

of this research is to identify and study the impact of the various macroeconomic factors on the auto indices of the Indian stock markets viz. BSE and NSE.

1.2 Contribution of Study

The stock market movements are an indication of the investors' confidence in various sectors of a country's economy. Generally when investors have less confidence about a particular industry, they will have less demand for these shares which will ultimately result in a reduction in the share prices (Ranjani & Dharmadasa 2018). Moreover they will look for alternative investment avenues like bank deposits, gold and so on which will have an impact on the economic structure of the country. On the other hand, many studies have found that various macroeconomic factors of a country also influence the stock index movements (Fama 1990). According to asset pricing theory (APT) of Stephen Ross, return from assets is a linear function of different macroeconomic variables where the responsiveness to changes in each variable is indicated by the corresponding coefficient in the model (Kevin 2015).Thus, the present study identifies the specific macroeconomic variables affecting the auto indices of the Indian stock market and also the extent of the impact in terms of long-run and short run relationship using ARDL co-integration techniques. Moreover, to the best of our knowledge, this is the first study to include both stock exchange indices (i.e S&P BSE auto index and Nifty auto index) and the macroeconomic variables to understand their relationship from an Indian context. The findings from this study will have implications for researchers, corporations, investors, portfolio managers and policy makers.

1.3 Aim & Research Questions

The main purpose of this research is to study the impact of selected factors like crude price, index of industrial production (as a proxy for GDP), inflation, exchange rate, gold prices and repo rate(as a proxy for interest rate) on the performance of the auto indices of the two major stock markets of India viz, BSE and NSE (Mohi-u-Din & Mubasher 2013; Joshi & Giri 2015; Misra 2018).

Hence this research study seeks to investigate the following questions:

Q1: How does crude price affect the BSE auto index and Nifty auto index?

Q2: How does IIP affect the BSE auto index and Nifty auto index?

Q3: How does inflation affect the BSE auto index and Nifty auto index?

Q4: How does exchange rate affect the BSE auto index and Nifty auto index?

Q5: How does interest rate (repo) affect the BSE auto index and Nifty auto index?

Q6: How does gold price affect the BSE auto index and Nifty auto index?

The above relationships could be complicated by the lagged values of the independent variables (Shahabuddin, 2009). Hence appropriate statistical tools (ARDL tests) have been employed for analyzing the data.

1.4 Structure of the Dissertation

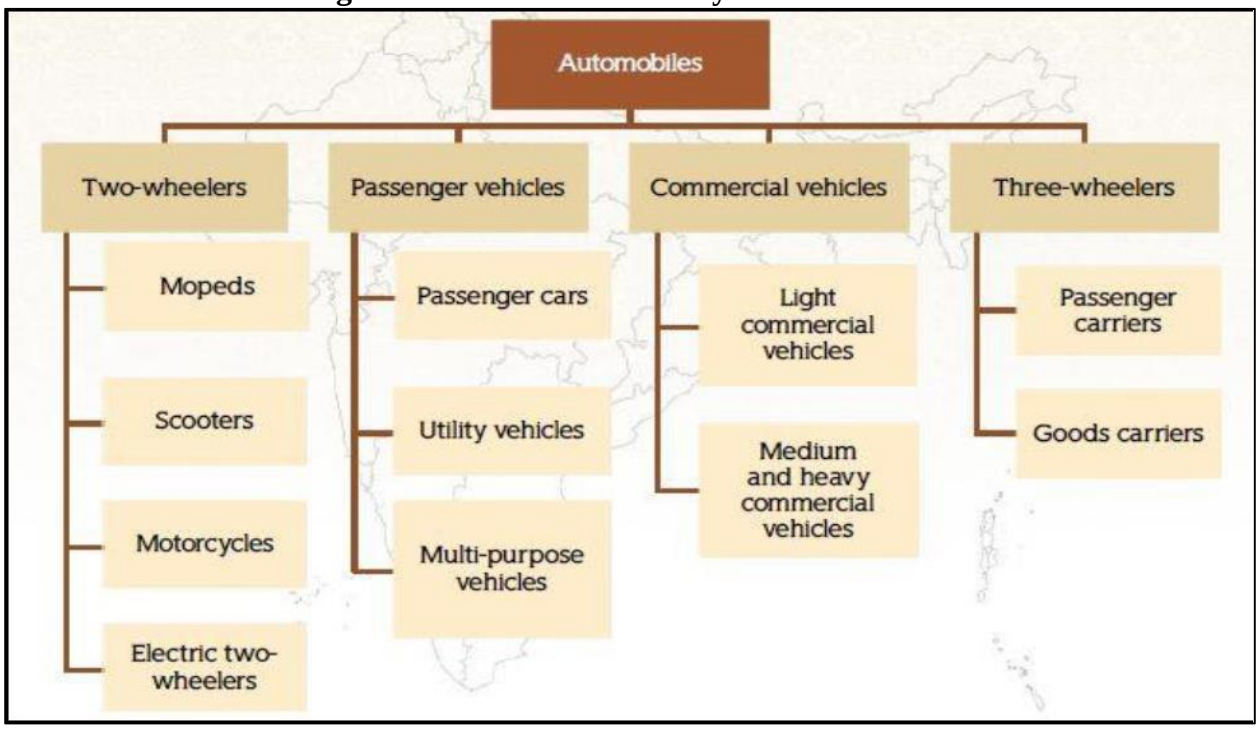
The remaining part of this dissertation report is structured as follows: Chapter 2 discusses about the automotive industry and stock markets in India. Chapter 3 reviews past studies and reports generated in similar fields to make connections between variables as well as to identify a possible gap in the literature. Chapter 4 highlights the various methods of data collection, hypothesis development as well as the methodology used for data analysis. Chapter 5 illustrates the findings. Chapter 6 summarizes the study offering recommendations to enhance the performance of auto stocks in India and also scope for future research. Through this chapter the researcher also tries to point out the limitations of the study.

CHAPTER 2: AUTOMOTIVE INDUSTRY & STOCK MARKETS OF INDIA

This chapter is organized in to two sub sections. In the first section, a brief overview of the Indian automotive industry is provided. Section two introduces the two major stock markets of India viz the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE).

2.1 INDIAN AUTOMOBILE INDUSTRY

Figure 1: Automotive Industry Profile of India



Source: India Brand Equity Foundation (IBEF 2015)

The automobile industry of India which includes both automobile manufacturing as well as automotive components, is one of the key contributors of economic growth in India (Miglani 2019). The auto sector, backed by strong governmental support, has carved a niche for itself among other manufacturing sectors of India. Automobiles produced in India cater largely to the demands

of the low and middle income population which makes it uniquely different from other automobile-producing countries.

In 2017, India became the world's fourth largest automobile market, and the demand for Indian vehicles continues to grow in the domestic and international markets. India was the sixth largest producer of automobiles globally with an average annual production of about 29 million vehicles in 2017–2018, of which about 4 million were exported. To meet the future needs of customers (including the electrical vehicles) and stay ahead of competition, manufacturers are now catching up on upgradation, digitization, and automation (Miglani 2019).

2.1.1 Market Size

Automobile industry is one of the major industries in India (Yadav, Sushil & Sagar 2015). India is the 4th largest manufacturer of commercial vehicles and passenger cars in the world behind China, Japan & Germany. Strong domestic demand along with supportive government policies enabled Indian automotive industry to become one of the global leaders in the field. According to OICA (International Organization of Motor Vehicle Manufacturers) India produced about 5.17 mn units (two wheelers excluded) in 2018. According to SIAM, the Indian Auto sector produced a total 30,915,420 vehicles including commercial vehicles, passenger vehicles, two wheelers three wheelers, and quadricycles in the period April 2018 to March 2019. The two-wheelers section which is driven by the populous middle class and young crowd dominates the market in terms of volume.

2.1.2 Industry Composition

The table given below shows the market share of the different types of vehicles in the automotive sector of India.

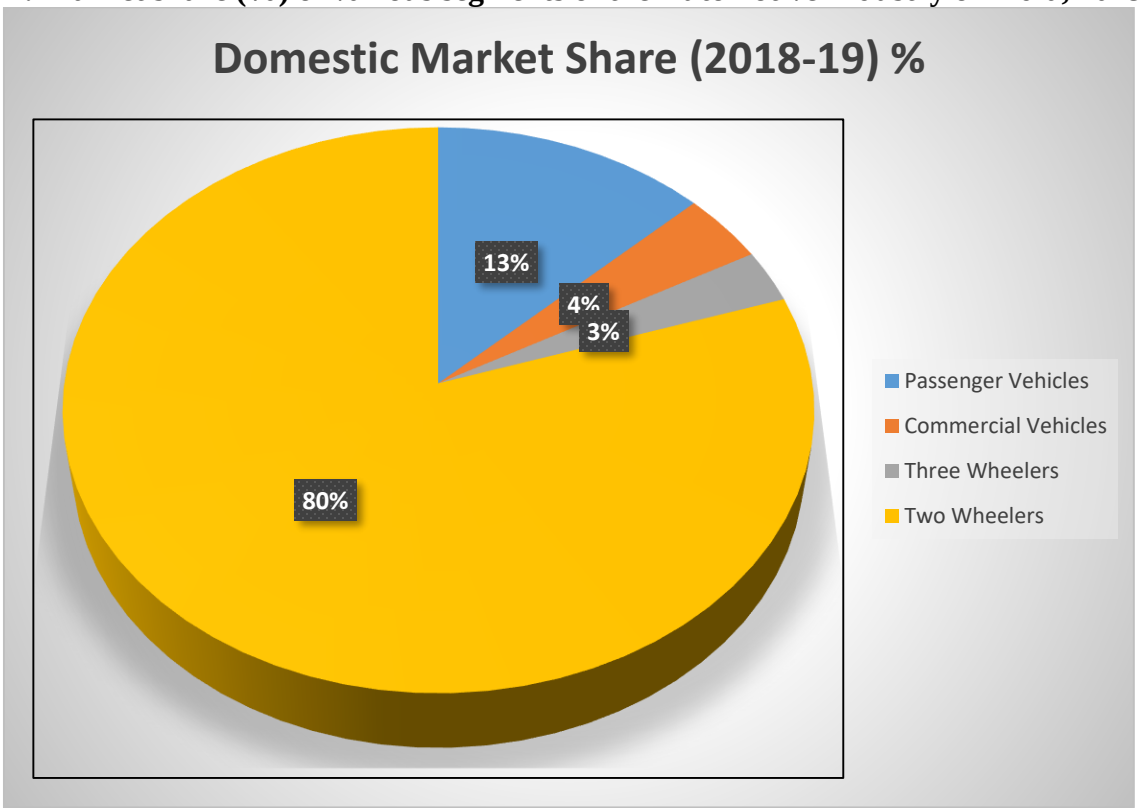
Table 1: Market share (%) of various Auto segments of India, 2018-19

Domestic Market Share (2018-19)	
Type of Vehicles	%
Commercial Vehicles	4
Three Wheelers	3
Two Wheelers	80
Grand Total	100

Source: Society of Indian Automobile Manufacturers (SIAM) [1]statistics

[1] *SIAM is the Apex National Body representing Indian automobile industry*

Fig 2: Market share (%) of various segments of the Automotive Industry of India, 2018-19



Source: Adapted from SIAM statistics

2.1.3 Importance to the Indian Economy

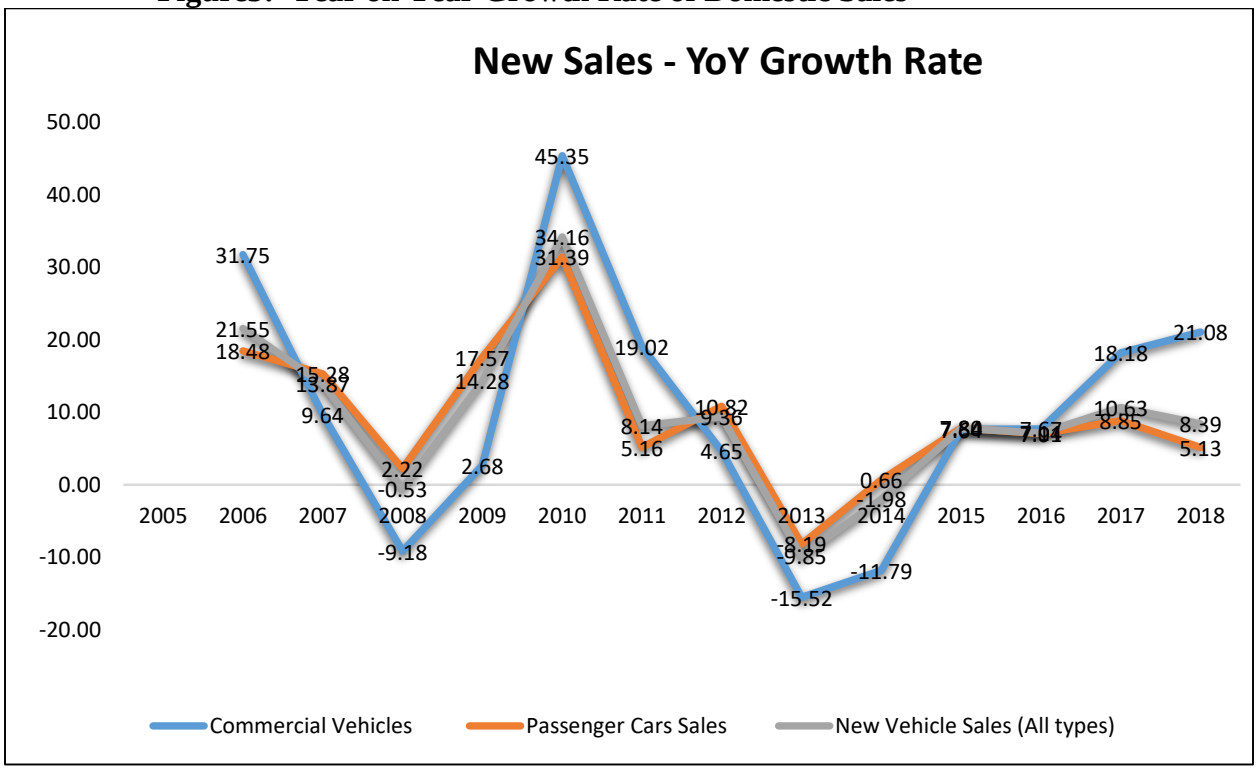
The auto industry is a key contributor to the nation's economy, contributing 7% to the country's GDP & 49% to the manufacturing sector output (Miglani 2019). It also provides direct and indirect employment to about 32 million people in the country. For well over two decades now, India has been an attractive investment destination for global automobile and component manufacturers due its buoyant economy, a largely young population, cheap labor and raw materials.

With over 1.3 billion people, India has the second largest population in the world. According to World Bank, the per capita GDP increased from US$ 1,357.56 in 2010 to US$ 2,009.98 in 2018. An ever-growing working population with a rapidly expanding middle-class has been one of the key drivers for the growth in automobiles in India (Miglani 2019). Factors like increasing disposable incomes and the presence of a large pool of skilled workers along with the fact that India has the second largest road network in the world (4.7 million kilometers), will continue to drive the demand for vehicles in the future. It is estimated that by 2030, India will add another 68 million households to its burgeoning middle-class which would drive an increased demand for automobiles. The number of registered motor vehicles per 1000 population in 2017 stood at 197 (Statista 2019) which when compared with 838 in the US points to a huge potential for increased penetration of private vehicle ownership in the years to come.

However, amidst all these expectations and predictions, the Indian auto industry has been sluggish and many sources reported its downturn in August 2019. According to SIAM, the Indian

automotive industry (domestic sales) reported de-growth of (-) 12.25 percent during April-August 2019 over the same period in 2018. But the total automobile exports grew by 1.42 percent where passenger vehicles and two wheelers exports rose by 4.13 percent and 4.52 percent respectively. Yet, commercial vehicles and three wheelers categories, registered de-growth of (-) 44.44 percent, and (-) 12.40 percent respectively during the same period when compared to the previous year. To highlight this scene, an year-on-year growth rate (2005-2018) of the domestic sales of Indian auto market is given in the graph shown below.

Figure3: Year on Year Growth Rate of Domestic Sales



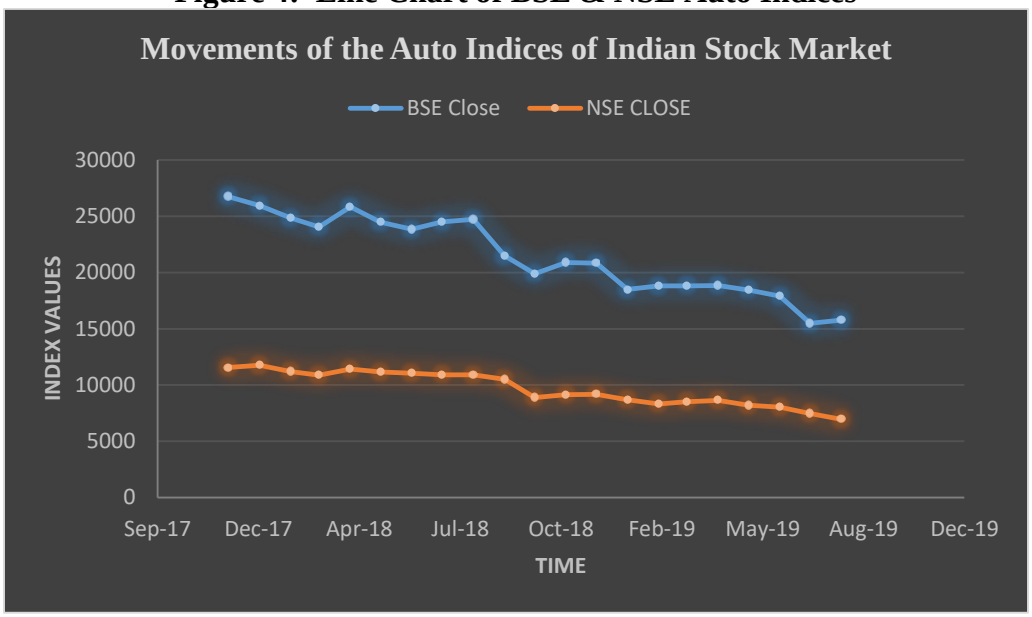
Source: Author' compilation from SIAM statistics

As seen from the figure above, the year-on-year growth rate for all the three segments in the Indian automotive market has been uneven since 2006. Both new vehicles and commercial vehicles

divisions registered de-growth (-0.53% and -9.18% respectively) during the year 2008. Passenger cars sales also plummeted during that year registering a growth rate of only 2.22% compared to the previous year. Nevertheless domestic sales as a whole increased drastically during the period 2008-2010. Yet, all these three divisions' sales has been consistently falling till 2014. All of them registered de-growth during the year 2013. There was a gradual growth in the sales figures from 2013 till 2017 even though these figures were almost stable during 2015-2016 with all the segments reporting year-on-year growth around approximately 8%. From 2017, we see a sharp fall in two segments i.e new vehicles sales and passenger cars sales showing a year on year growth rate of 8.39% and 5.13% compared to 10.63% and 8.85% of the previous year. On the contrary, commercial vehicles showed an increase in growth (21.08%) over year 2017 (18.8%) but that is only marginal (2.28%).

The repercussions were seen on the movement of the auto indices of both of the major Indian stock markets viz BSE India and NSE India. To better understand the situation, the movement of BSE Auto index and Nifty auto index during the period Dec 2017 and August 2019 is plotted below.

Figure 4: Line Chart of BSE & NSE Auto Indices



As it is evident from the above graph, the auto indices of both BSE and NSE has been falling since Dec 2017 with BSE Auto index dropping 41.1% and Nifty auto index dipping to 39.7% in August 2019 when compared to its value in December 2017.

2.2 STOCK MARKETS OF INDIA

The Indian securities market has become one of the most dynamic and efficient securities market in Asia today (Kevin 2015). It conforms to international standards in terms of operating efficiency. All the stock exchanges in the country, are deploying computerized trading system which facilitates screen-based trading. Hence, the stock markets in India today, uses the state of the art information technology tools to provide efficient and explicit trading, clearing and settlement systems at par with international standards.

2.2.1 The Bombay Stock Exchange (BSE)

The Bombay Stock Exchange (earlier called as Native Share and Stockbrokers Association) which is the oldest stock exchange in Asia was formed by a group of stock brokers in 1875(Kevin 2015). The association drew up codes of conduct for brokerage business and mobilized private funds for investment in the corporate sector.

2.2.2 The National Stock Exchange (NSE)

After the liberalization of Indian economy during 1990s, the National Stock Exchange (NSE) was incorporated in 1992 to raise the level of Indian stock market trading system to international standards. NSE was promoted by the top financial institutions of the country, viz ICICI, IDBI, IFCI, all insurance corporations, selected commercial banks and others following the recommendations of the Pherwani committee (the top powered committee on stock exchanges in India). NSE started functioning in 1994 (Kevin 2015).

National Exchange for Automated Trading (NEAT), the trading mechanism of NSE is a state-of-the-art client-server based application. The NSE also uses satellite communication technology for trading. The NSE has brought about unparalleled transparency, speed and efficiency, safety and market integrity. In this process the NSE has become the largest stock exchange in India, relegating the BSE to the second place.

As of now, there are 23 stock exchanges in the country. The Securities and Exchange Board of India (SEBI) manages and regulates these stock exchanges. Four out of them are considered as the national stock exchanges, viz, NSE, BSE, OTCEI (Over the counter Exchange of India) and ISE (Inter-connected Stock Exchange of India); the remaining 19 are regional stock exchanges located in important cities of the country.

Most of the trading in securities in the country are transacted through the two largest stock exchanges, viz, the NSE and the BSE which have trading terminals all over the country.

2.2.3 The Auto Indices of BSE and NSE stock exchanges

A sectorial index of a stock market is a representation of the entire sector and thus keep track of the changes in the market over time (Joshi & Giri 2015) . The S&P BSE Auto & NIFTY Auto Index are two key indices that monitor the automotive industry in India. The S&P BSE Auto index is comprised of the constituent companies of the S&P BSE 500 that are categorized as members of the transportation equipment sector as defined by the BSE industry classification system. The NIFTY Auto Index is computed using the free float market capitalization method with a base date of January 1, 2004 indexed to a base value of 1000. It is designed to reflect the behaviour and performance of the Indian automobile sector.

2.2.4 S&P BSE Auto Index

The S&P BSE SENSEX consists of 30 companies listed in the Bombay stock market. These constituents are from various industries such as telecommunications, information technology, pharmaceuticals, energy, capital goods, metals and mining, consumer discretionary, and finance. The constituents of the index are selected on the basis of market capitalization, trading frequency, industry representation, and reputation. The index is managed by the Index Committee of the Bombay Stock Exchange Limited and was formed in 1986. The S&P BSE SENSEX is reviewed on a quarterly basis(S&P Capital IQ 2019). A list of companies that are listed in S&P BSE Auto index is provided in Table2.

Table 2: Companies listed in the S&P BSE AUTO Index

	Scrip Code	COMPANY	ISIN No.
1	500877	Apollo Tyres Ltd	INE438A01022
2	500477	Ashok Leyland Ltd	INE208A01029
3	532977	Bajaj Auto Ltd	INE917I01010
4	502355	Balkrishna Industries Ltd	INE787D01026
5	500530	Bosch Ltd	INE323A01026
6	500480	Cummins India Ltd	INE298A01020
7	505200	Eicher Motors Ltd	INE066A01013
8	500086	Exide Industries Ltd	INE302A01020
9	500182	Hero MotoCorp Ltd	INE158A01026
10	500520	Mahindra & Mahindra Ltd	INE101A01026

11	532500	Maruti Suzuki India Ltd	INE585B01010
12	517334	Motherson Sumi Systems Ltd	INE775A01035
13	500290	MRF Ltd	INE883A01011
14	500570	Tata Motors Ltd	INE155A01022
15	532343	TVS Motor Co Ltd	INE494B01023

Source: BSE website (Indices Watch - S&P BSE AUTO 2019)

2.2.5 Nifty Auto Index

Nifty50 Index consists of 50 companies whose stocks are traded on the National Stock Exchange of India (NSEI). The constituents of the index are the exchange's 50 largest companies and together they account for about 60% of the total market capitalization of NSE. In addition to market capitalization, inclusion in the index is also subject to factors such as industry representation, liquidity and share float. Nifty50 is managed by India Index Services and Products Ltd., which is a joint venture between NSE India and CRISIL (S&P Capital IQ 2019).

The Nifty Auto Index is tailored to reflect the behavior and performance of the Automobiles sector which includes manufacturers of cars & motorcycles, heavy vehicles, auto ancillaries, tyres, etc. The Nifty Auto Index is composed of 15 stocks that are listed on the National Stock Exchange. Table 3 below lists these companies with their symbols and ISIN[2] codes.

[2] *ISIN stands for International Securities Identification Number*

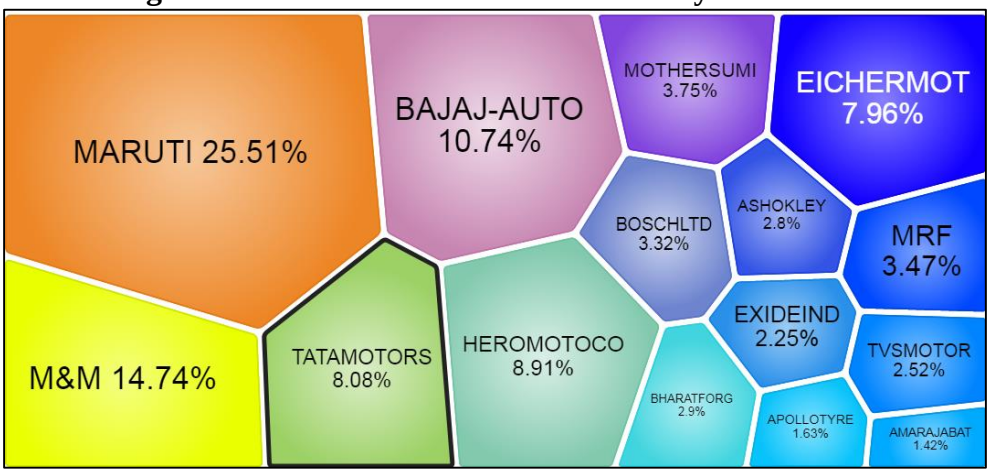
Table 3: Companies listed in the NSE Nifty AUTO Index

	Company Name	Symbol	ISIN Code
1	Amara Raja Batteries Ltd.	AMARAJABAT	INE885A01032
2	Apollo Tyres Ltd.	APOLLOTYRE	INE438A01022
3	Ashok Leyland Ltd.	ASHOKLEY	INE208A01029
4	Bajaj Auto Ltd.	BAJAJ-AUTO	INE917I01010
5	Bharat Forge Ltd.	BHARATFORG	INE465A01025
6	Bosch Ltd.	BOSCHLTD	INE323A01026
7	Eicher Motors Ltd.	EICHERMOT	INE066A01013
8	Exide Industries Ltd.	EXIDEIND	INE302A01020
9	Hero MotoCorp Ltd.	HEROMOTOCO	INE158A01026
10	MRF Ltd.	MRF	INE883A01011
11	Mahindra & Mahindra Ltd.	M&M	INE101A01026
12	Maruti Suzuki India Ltd.	MARUTI	INE585B01010
13	Motherson Sumi Systems Ltd.	MOTHERSUMI	INE775A01035
14	TVS Motor Company Ltd.	TVSMOTOR	INE494B01023
15	Tata Motors Ltd.	TATAMOTORS	INE155A01022

Source: NSE website (NSE India 2019)

Additionally, Figure5 given in the next page presents the share distributions among these companies.

Figure 5: Sectorial Distribution of the Nifty Auto Index



Source: Adapted from NSE website (NSE India 2019)

The figure above shows the sectorial distribution of shares of the Nifty auto index. Maruti Ltd leads the sector with 25.51% of shares, followed by Mahindra & Mahindra (14.74%) and Bajaj-Auto Ltd (10.74%). All the other players have only less than 10% shares in the Nifty auto sector.

CHAPTER 3: LITERATURE REVIEW

Ever since the introduction of stock exchanges, many studies have been conducted across the globe to find the association between their performance and various macroeconomic indicators. Minor variations in the macroeconomic environments are seen to cause rapid movements in the stock markets (Joshi & Giri 2015). Hence it has been a chosen area of investigation among researchers, academicians, policy makers and economists. A review of the past studies conducted in this context are as follows:

Mazzucato & Semmler (1999) collected industry level and company level annual data to conduct an empirical analysis of the US automobile industry to explore the extent to which volatility in market shares is correlated with the volatility of stock prices and with the price-earnings level. It was seen that industry specific factors like life cycle affect them as excess volatility of both these factors were seen to be higher during the initial phase of each firm's history. The researchers concluded by recommending the usage of Schumpeter literature as a useful framework for similar future researches.

In another study, Shahabuddin (2009) investigated the impact of various economic factors like durable industrial demand, discount rate , durable personal consumption, personal consumption, non-durable industrial goods demand, GDP, GNP, leading economic indicators, population, M1, M2 and M3 on automobile sales in the US using step-wise regression. Here automobile sales was categorized into domestic and foreign car makers. Even though the results revealed strong correlation between those variables, the association with that of domestic car sales turned out to be weak. Both the lagged and unlagged independent variables showed same strength of relationship with the selected response variables.

In another research, Srivastava (2010) investigated the impact of change in macroeconomic factors on the Indian stock market using the Johansen's co-integration test. This study revealed that Indian stock markets are influenced by domestic macroeconomic factors when compared to global factors in the long run. And these macroeconomic factors include interest rate, wholesale price index and industrial production.

Similarly, Muhammad, Hussin & Razak (2012) examined the impact of economic variables viz inflation, GDP, unemployment rate and interest rate on automobile sales in five ASEAN countries namely Philippines , Malaysia, Singapore, Indonesia and Thailand for the period between 1996 and 2010. The results shows that GDP has positive association with car sales. On the other hand interest rate, unemployment rate and inflation were seen to have a negative association with car sales. Panel error-correction model was employed to implement the long term and short term correlation between variables.

A research conducted by Ahmadian, Hassan and Regassa(2015) asserted that the most directly affected sector resulting from unstable oil prices is the transportation sector and the automobile industry in particular. The study had cited the example when once the US auto industry was on the verge of extinction due to enormous surge in the oil prices which nearly froze the demand for their domestically produced vehicles.

In another research, Gaspareniene & Remeikiene (2014) used correlation and multiple regression analysis to determine the link between macroeconomic factors that influenced the EU automotive industry during the period of global financial crisis. The results indicated that automobile production is strongly influenced by its demand (i.e new vehicle registration) and the GDP. It also found a moderate correlation between public debt and automobile production. They could not

logically explain the relationship between oil price and steel price index with automobile production and hence recommended applying Vector Error Correlation Model (VECM) for a comprehensive analysis.

In a study conducted by Yadav, Sushil and Sagar (2015) to explore the hierarchical structure and linkages of multiple strategic factors affecting the auto industry performance in India, by (Yadav, Sushil & Sagar 2015)(Yadav, Sushil & Sagar 2015)(Yadav, Sushil & Sagar 2015)(Yadav, Sushil & Sagar 2015)adopting a flexible strategy game-card approach . They adopted thematic content analysis and total interpretive structural modeling (TISM) to analyze conducted semi-structured interviews and also to identify the performance related strategic factors respectively. Furthermore, case-lets and statistical analysis were employed for subsequent validation of the model. Their results proposed a strategic performance management model for Indian automobile enterprises that can be considered as a conceptual scheme which enables one identify the leading and lagging factors of performance.

During the same year, Geetha & Swaaminathan (2015) attempted to determine whether firm specific factors has a role in the automobile and IT industry stocks in India, factors like P/E ratio, EPS, dividend yield and book value were used for the analysis. It was found that all factors except dividend per share are influencing the market value of the stock.

On the other hand, Sinha & Kohli (2015) explored the effect of exchange rate (USD/INR) on BSE Sensex, BSE Oil & Gas index and BSE IT index during the time frame January 2006 to March 2012 to estimate the exchange rate dynamics in India. But they could not establish any relationship between the exchange rate (US/INR) and the stock index returns. Other explanatory variables like

interest rate, inflation and current account deficit seem to have a negative relationship with exchange rate.

A recent study by Büyük, Otomobil & Ülkedeki (2018) investigated the macroeconomic dynamics of real GDP, GDP per capita, inflation ,automobile production, exchange rate and gasoline price on the automobile sales among four topmost auto production countries viz China, USA, Japan, and Germany by using Ordinary Least Squares (OLS) and Fixed Effect Models (FEM). The findings revealed that real GDP, gasoline price , car production have positive linkage with car sales while change in exchange rate, GDP per capita and inflation and cause the opposite.

In their research, Nanda & Panda (2018) studied the impact of firm-specific (total asset, debt/equity, current ratio) and macroeconomic indicators (net exports, net imports, volatility of exchange rate , real and nominal effective exchange rates, , index of industrial production and interest rate) on the profitability of Indian manufacturing firms before and after crisis during the period 2000 -2015. Generalized least square regression with random-effects design and vector auto-regression for the standard panel data was employed on annual data of 173 listed firms in S&P BSE Industrial Index. The return on assets (ROA) and the net profit margin (NPM) were considered as proxy for corporate profits. The study claims that firm-specific variables and exchange rate can be considered as potential indicators of manufacturing firm profitability. However, exchange rate is no better predictor in the short run when compared to the long run. Even more, the study also posits that nominal exchange rate index is better at predicting profitability than real exchange rate.

To analyze the drivers, strategies and contingent factors impacting the volume flexibility of Indian firms belonging to the automobiles and allied products, electrical and fashion apparel industry, Mishra (2018) adopted a multiple case study approach. Based on the qualitative data collected from northern India, the study suggested that uncertainties associated with demand, technology, competitors, suppliers and macroeconomic indicators as the drivers of flexibility while strategies of the firm, competitive behavior, nature of demand, product life cycle and features of end product as the contingent factors.

Recently, Misra (2018) sought to examine the possibility and strength of linkages, between Sensex and a few macroeconomic factors for the period April 1999-March 2017. Through various statistical tests like co-integration, granger causality and vector error correction methods, it was found that there is a long-run causal relationship between money supply, inflation, index of industrial production (IIP), gold prices, interest rates, exchange rate, foreign institutional investment and BSE Sensex. Additionally, the study also identified a short run causality between inflation and Sensex and also between money supply and Sensex.

Very recently, Tambade, Singh and Modgil (2019) conducted an extensive literature review in order to identify the dimensions of competitiveness and to build a suitable conceptual framework for the Indian auto-component industry. About 30 variables under 7 constructs (factor conditions, employee engagement, business environment, industry structure, firm strategy, demand conditions) were identified to be the potential indicators of competitiveness. The study also mentioned about the development and validation of a survey instrument through these factors.

Table 4 summarizes the above review of literature.

3.1 Research Gap

After reviewing the literature, it is evident that there had been many studies done in the past connecting stock market performance and macroeconomic indicators in many countries. However, there exist a dearth of research specifically aimed at finding a possible link between these macroeconomic factors and the auto indices in the Indian stock market. Moreover, the above studies have reported inconsistent results. Given the current scenario in the automobile industry, and its repercussions in the stock markets, the author feels it is a good idea to explore whether any of these macroeconomic factors have a role in this. Hence this study is an endeavor to investigate such a link if any existing between the auto indices (BSE auto index & Nifty auto index) of the Indian stock market and macroeconomic variables like crude price, exchange rate, index of industrial production, inflation, interest rate, repo rate and gold price. The results of the study will have major policy implications.

Table 4: Review of Literature (1999-2019)

	Author	Objective	Place	Methodology	Findings
1	Mazzucato & Semmler(1999)	To explore possible relationship between market share instability and volatility of stock price in the automobile Industry To find out to what extent the above relationship is connected to industry specific factors	US	Mean, Standard deviation, variances and charts	Excess volatility is partially influenced by Industry-specific factors.
2	Shahabuddin (2009)	To study the performance of automotive industry in relation to various economic and demographic variables	US	Step wise regression	Identified a strong linkage between the independent variables and foreign car sales; weak correlation with that of domestic car sales

3	Muhammad, Hussin, & Razak (2012)	To examine the impact of macro factors on automobile sales in five ASEAN countries namely Singapore, Indonesia, Thailand, Philippines and Malaysia from 1996 - 2010.	Malaysia	Mean group and pool group analysis using panel method	Significant correlation was reported between the independent variables and automobile sales. Each country is affected by a different variable in the short run.
4	Ahmadian, Hassan and Regassa(2015)	To study the impact of the volatility and trends in oil prices on the evolution of the auto industry for about ten years.	US	Trend Analysis using graphs	Rise in oil prices will have a conspicuous effect on the auto industry.
5	Gaspareniene & Remeikiene (2014)	To identify and evaluate the factors that affect the automobile industry in the EU during financial crisis.	Italy	Correlation and Multiple Regression	New vehicle registration and GDP have significant positive impact on the EU automotive production.

					Public debt has a positive and moderate correlation GDP & new automobile registration explained 60 per cent of the changes of automobile production in the EU.
6	Geetha & Swaaminathan (2015)	To analyze whether company specific factors influence stock price movements in the automobile and IT sectors of BSE and NSE	India	Ratio Analysis (criticism)	Evidence for significant relationship between book value, earnings per share and price earnings ratio and the stock prices. Dividend per share has no effect on the stock prices
7	Yadav, Sushil and Sagar(2015)	To identify the strategic factors and their relationships to make out the strategic performance	India	Flexible strategy game-card, Content analysis,	Proposed a strategic performance management model for

		management issues in the automobile industry		TISM, Case-lets and statistical analysis	the Indian auto industry
8	Büyük, Otomobil & Ülkedeki (2018)	To find out the effect of six macroeconomic variables on the automobile sales in China, USA, Japan, and Germany		OLS, Chow Test, Normality Test and Multi collinearity	Real GDP, car production and gasoline price have positive link towards car sales. Change in GDP per capita, exchange rate and inflation is seen to have a negative impact. Some results look inconsistent with previous findings.
9	Tambade, Singh & Modgil (2019)	To explore the dimensions of competitiveness and their precedents and to build a model of competitiveness for	India	Literature Review	30 variables were identified as potential indicators of competitiveness.

		the Indian auto-component industry by			
10	Nanda & Panda (2018)	To examine the impact of firm-specific (total asset, debt/equity, current ratio) and macroeconomic indicators on the profitability of Indian manufacturing firms before and after crisis during the period 2000 -2015.	India	Panel least square method & vector auto regression model	Firm-specific and exchange rate variables are potential indicators of manufacturing firm's profitability in India. Size and liquidity is directly proportional to profitability whereas leverage is inversely proportional. Volatility of exchange rate increases profitability in the long run.
11	Mishra (2018)	To analyze the drivers, strategies and contingent factors impacting the volume flexibility of Indian firms	India	Multi Case Study	Suggests that uncertainties associated with demand, technology,

		belonging to the automobiles and allied products, electrical and fashion apparel industry			competitors, suppliers and macroeconomic indicators are the drivers of flexibility while strategies of the firm, competitive behavior, nature of demand, product life cycle and features of end product are the contingent factors.
12	Misra (2018)	To explore the strength of link if any exist between BSE Sensex and macroeconomic variables for the period April 1999-March 2017.	India	Johansen Co-integration, Granger Causality and Vector Error Correction	Long-run causality between the macroeconomic variables and BSE Sensex. Short run causality between Inflation and BSE Sensex and Money Supply and BSE Sensex.

13	Srivastava (2010)	To investigate the impact of change in macroeconomic factors on the Indian stock market.	India	ADF & PP Tests, LM Test Johansen's Co-integration test	In the long run, the main macroeconomic indicators of stock market are IIP, WPI and interest rate.
14	Sinha & Kohli (2015)	To find out the link between forex rate, three market indices of India, economic factors and real GDP between1990-2011.	India	ADF test, Least Square Regression	No association between exchange rate [USD/INR] and stock returns. Exchange rate showing negative association with the other variables taken.

CHAPTER 4: DATA AND METHODOLOGY

4.1 Data Description

In this research study, time series data ranging from January 2017 to August 2019 on a monthly basis is used for the empirical analysis. After reviewing past literature related to the performance of automobile industry, and also by interacting with senior managers working in the same industry, six macroeconomic variables were initially selected as the independent variables for the study. These include price of crude oil (CRUDE), exchange rate (ER) , index of industrial production (IIP) as a proxy for GDP, consumer price index (CPI) as a proxy for inflation, gold price (Gold Price) and repo rate (REPO) as a proxy for interest rates. The auto indices of NSE i.e Nifty Auto index (NiftyAuto) and BSE i.e S&P BSE Auto index (BSEAUTO) are taken as the dependent variables. The data series except repo rate, has been plotted on a logarithmic scale so that the changes in these variables represent relative changes. A brief discussion on the data collected, their sources and hypothesis development is given below.

4.2 MEASUREMENTS OF VARIABLES AND HYPOTHESIS DEVELOPMENT

4.2.1 Dependent Variables

Nifty Auto Index (Nifty Auto) & S&P BSE Auto Index (BSEAUTO)

The closing prices of the auto indices of the two stock markets viz NSE and BSE were collected from the respective websites during the period January 2017 to August 2019. Monthly data available from BSE was used as such; whereas from NSE, the daily closing prices of the auto index was averaged on a monthly basis and made available for the analysis.

4.2.2 Independent Variables and Hypotheses

4.2.2.1 Crude Price (CRUDE)

West Texas Intermediate (WTI) crude price is the standard for American oil prices and Brent crude price is the international benchmark price used by Organisation of Petroleum Exporting Countries (OPEC). The quantity of oil is measured in the international market in barrels, where one barrel is equivalent to 42 US gallons. This factor has been used in several studies (Ahmadian, Hassan & Regassa 2015; Gupta & Goyal 2015). Many sources have reported the preference of Indian refiners towards oil prices linked to Brent than WTI, even though the latter seems to be somewhat cheaper (Mishra 2011). Hence for this study, monthly data related to spot price of Brent (dollars per barrel) downloaded from the website of US Energy Information Administration (EIA) has been used. Gupta and Goyal (2015) found a significant positive relationship between oil price and stock prices in Indian context. However, Ray (2012) suggests a negative association between oil prices and Indian stock market. Even though, a surge in oil prices affect the entire economy of a nation, the most adversely hit industry is the transportation sector, the automobile industry in particular (Ahmadian, Hassan & Regassa 2015). Recently, Elian and Kisswani (2017) also found a negative relationship between oil prices and Kuwait stock market.

Thus we can hypothesize:

H1: There is a negative association between crude price and BSE auto and Nifty auto indices, ceteris paribus.

4.2.2.2 Exchange Rate (ER)

The price of one country's currency in terms of another country is called the exchange rate (Ranjani & Dharmadasa 2018). Daily data pertaining to the exchange rate (USD-INR) downloaded from the RBI website for the period Jan 2017 to Aug 2019 was averaged on a monthly basis to get the values. Exchange rate may affect the stock prices in two ways; a direct effect through multi-

national companies and an indirect effect through domestic companies. Some authors contend that exchange rate fluctuations can have a prominent impact on the firm value as they affect the input and output prices, terms of competition, and the value of firm's assets and liabilities denominated in foreign currencies (Joshi & Giri 2015). A decrease in the home currency increases the exports and makes imports costlier. Previous studies have revealed conflicting results on their studies related to exchange rate movements and stock prices. Joshi and Giri (2015) claims a positive relationship between exchange rate and BSE Sensex. On the other hand, few studies (Sinha & Kohli 2015; Srivastava 2010) could not find any relationship between exchange rate and Sensex. However, a recent study reported negative bidirectional causality between real exchange rate and stock prices (Türsoy 2017). More recently, Ranjani and Dharmadasa (2018) also claims a negative relationship between exchange rate and SriLankan stock market index. Thus we can hypothesize:

H2: There is a negative association between exchange rate and BSE auto and Nifty auto indices, ceteris paribus.

4.2.2.3 Index of Industrial Production (IIP)

GDP is a measure of the total production of all goods and services in a country during a stipulated time period usually, one year. GDP growth rate is a significant indicator of the economic performance of any country. In India, during 1995-2003 average GDP was around 6% and from 2004 onwards, it has been slightly above 8%. Many authors have tried to explore the association between economic growth and stock prices (Fama 1990; Joshi & Giri 2015). The results from these studies indicate a strong positive correlation between the two variables. A higher growth rate is considered favorable to the stock market, other things being equal. In this study, Index of Industrial Production is used as a proxy for GDP because in India the latter is available only on a quarterly

basis. Past studies indicate that IIP has a very high positive correlation with GDP (0.97), and is a suitable indicator of economic activities in India (Sethi 2008; Joshi & Giri 2015; Gupta & Goyal 2015). Even more, many past studies found a positive association between IIP and Indian stock market indices (Srivastava 2010; Paramati & Gupta 2011; Ray 2012; Giri & Joshi 2017).Hence we can hypothesize:

H3: There is a positive association between IIP and BSE auto and Nifty auto indices, ceteris paribus.

4.2.2.4 Inflation (CPI)

According to Samuelson and Nordhaus (2010), "By inflation, we mean a time of generally rising prices." When inflation refers to a rise in general price level, the rate of inflation is the rate of change of general price level (Kumar & Gupta 2007). Inflation is calculated using different price indices in India. The Wholesale Price Index (WPI) and the Consumer Price Index (CPI) are the two important indices that are commonly chosen for any empirical analysis (Goel 2018). This study uses CPI and the required data was downloaded from RBI website. CPI inflation is defined as a year-on-year log difference of the CPI index with base year 2012=100. The effect of inflation on the corporate sector is quite mixed. Those industries that have a strong market base and which do not come under the scope of price control may benefit. But those industries having a weak market base and that come under the scope of price control may lose. Overall, a moderate level of inflation influences stock market positively. Similar previous studies also found positive correlation between inflation and stock prices (Mohi-u-Din & Mubasher 2013; Joshi & Giri 2015). Thus we hypothesize:

H4: There is a positive association between inflation and BSE auto and Nifty auto indices, ceteris paribus.

4.2.2.5 Gold Price

Monthly gold prices ($/troy oz) for this study, were taken from World Bank commodity price data sheet downloaded from World Bank website. Traditionally, gold is considered as a safe haven for investment in India. Gold price is expected to increase when equity prices plummet and traders seek gold as an alternate source of investment (Maierbrugger, 2015).Howbeit, gold prices have been declining since the second half of 2012 and it is said that the returns from gold is not comparable with the returns from asset classes like stocks. Nevertheless, gold is considered to act as a hedge against inflation, offering high liquidity and alleviates risk in the portfolio (George, 2019). Most of the research studies (Ray 2012; Joshi & Giri 2015; Misra 2018) conducted in Indian context reveals that there exists a negative relationship between gold prices and stock indices. Hence we can hypothesize:

H5: There is a negative association between gold price and BSE auto and Nifty auto indices, ceteris paribus.

4.2.2.6 Repo Rate (REPO)

According to Brue, McConnel and Flynn (2018), "Interest is the payment for the use of money or for the use of loanable funds." Or in other words, interest rate is referred as the amount charged by a lender to a borrower for the use of his assets (Ranjani & Dharmadasa, 2018). It is generally expressed as a percentage of the principal amount. In India, when commercial banks borrow money

from RBI, they are charged an interest which is called as the repo rate. For the current study, this rate (%) on a monthly basis was collected from the RBI website during the period Jan 2017 to Aug 2019.

Traditionally, interest rates in India were quite high and most of these rates in the organized sector were regulated. A rise in interest rate leads to a fall in corporate profitability. It also rises the discount rate employed by the equity investors. Both of these will have negative impact on stock prices. The study conducted by Srivastava (2010) also proved the same. In addition, Muhammed et. al (2012) also found a negative relationship between interest rate and automobile sales among ASEAN countries. Hence we can hypothesize:

H6: There is a negative association between repo rates and BSE auto and Nifty auto indices, ceteris paribus.

4.3 EMPIRICAL MODEL

The model is based on previous studies (Srivastava 2010; Joshi & Giri 2015; Sinha & Kohli 2015; Giri & Joshi 2017; Misra 2018) where the linkage between macroeconomic variables and stock market index has been investigated. The following general specification has been employed in this study to empirically test the impact of the selected macroeconomic variables on the auto indices of the Indian stock market.

Model-1

$$LBSEAUTO = \alpha_0 + \alpha_1 LCRUDE + \alpha_2 LER + \alpha_3 LIIP + \alpha_4 LCPI + \alpha_5 LGoldPrice + \alpha_6 REPO + \varepsilon_t \quad \text{..... (4.3.1)}$$

Model-2

$$LNiftyAuto = \alpha_0 + \alpha_1 LCRUDE + \alpha_2 LER + \alpha_3 LIIP + \alpha_4 LCPI + \alpha_5 LGoldPrice + \alpha_6 REPO + \varepsilon_t \quad \text{..... (4.3.2)}$$

where, LBSEAUTO is the auto index of the BSE Auto Sector, LNiftyAuto is the auto index of the NSE Auto Sector, LCRUDE is the crude oil (Brent) prices, LER is the exchange rate (USD/INR), LIIP is the Index of Industrial Production which is used as a proxy for GDP, LCPI is the Consumer Price Index which measures the retail price inflation, LGoldPrice is the gold prices and REPO is the inter-bank rate in India which is taken as the interest rate in this study.The prefix L indicates that the model uses data in the log form. After running an ARDL regression with Akaike Information Criterion (AIC) for identifying optimal lags for Model-1 above, LCPI and LGoldPrice were found to be collinear. Karl Pearson's correlation coefficient (ϱ) between the two was found to be 0.458 significant at 5% level. Similar analysis with Model-2 identified REPO and

LGoldPrice to be collinear. In this case, Karl Pearson's correlation coefficient (ϱ) between the two was found to be -0.840 significant at 5% level. Hence the variable, LGoldPrice was eliminated from both models for further analysis.

As stated before, this study attempts to empirically estimate the impact of the above macroeconomic variables on the auto indices of BSE and NSE using the time series concepts and methods detailed in the following sections. Monthly data from Jan 2017 to Aug 2019 of these variables were compiled from multiple sources. Some authors contend that monthly data is better at capturing short run fluctuations of the variables (Joshi & Giri 2015). Hence, in the present context these explanatory variables are expected to have some impact on the performance of the auto indices of the BSE and NSE.

4.4 TIME SERIES DATA AND COMPONENTS

As this research study uses time series data, a brief review of the important concepts in time series data and time series analysis is provided in the following sections.

4.4.1 Definitions

According to Asteriou and Hall (2007), a time series data set comprises of observations of one or more variables over time. It is arranged chronologically and have different frequencies like daily, weekly, monthly, quarterly, yearly etc. Or in other words, it is a series of data that gets recorded periodically (Kocenda & Cerny 2015). According to Adhikari and Agrawal (2013), a time series data is defined as a set of vectors Y(t) where t represents the time passed by and can take values like 0,1,2 ,….. Here, Y(t) is considered as a random variable.

A univariate time series consists of records pertaining to a single variable whereas multivariate time series consists of data pertaining to more than one variable. Furthermore, a time series can be continuous or discrete (Adhikari & Agrawal 2013). A discrete time series consists of observations recorded at discrete points of time (for e.g. daily or weekly or monthly). On the other hand, in a continuous time series, observations are measured at every point in time (for e.g. temperature readings in degree Celsius).

This study makes use of discrete time series data of the identified variables on a monthly basis.

4.4.2 Components and Models

Generally, a time series is composed of four main components viz. trend, cycle, seasonality and irregular variations. Trend refers to a general tendency of a time series to increase, decrease or stagnate over a long period of time. Or in other words, it is a long term movement in a time series. Seasonal variations refer to the fluctuations in a time series with in a year during a season. “The cyclical variation in a time series describes the medium-term changes in the series, caused by circumstances, which repeat in cycles. The duration of a cycle extends over longer period of time, usually two or more years. Most of the economic and financial time series show some kind of cyclical variation. For instance, a business cycle consists of four phases, viz. prosperity, decline, depression and recovery. Irregular or random variations in a time series are caused by unpredictable influences, which are not regular and also do not repeat in a particular pattern. For e.g. war, natural calamities, pandemic etc. There is no defined statistical technique for measuring random fluctuations in a time series” (Adhikari & Agrawal 2013).

Two different types of models are used in a time series analysis to incorporate the effect of the above mentioned four components. “A multiplicative model is based on the view that the four components of a time series are not necessarily independent and they can affect one another; whereas in the additive model it is assumed that the four components are independent of each other” (Adhikari & Agrawal 2013). This is illustrated below.

Multiplicative Model: $Y(t) = A(t) \times B(t) \times C(t) \times V(t)$.

Additive Model: $Y(t) = A(t) + B(t) + C(t) + V(t)$.

Where, Y(t) refers to the data that is being recorded and T(t) , A(t) , B(t), C(t) and V (t) are the trend, seasonal, cyclical and irregular variation at time t respectively.

4.5 KEY CONCEPTS IN TIME SERIES ANALYSIS

The process of fitting a time series to a suitable model is called as time series analysis (Hipel & McLeod 1994). There are various approaches to time series analysis. One of the most popular method is to fully explore the dynamic structure of the data (Asteriou & Hall 2007). Broadly speaking, time series analysis is commonly discussed within two categories, vis. time series forecasting and dynamic modelling. Univariate analysis is not concerned with building of a model or understanding the relationship between variables, but aims at developing efficient models, which are able to forecast well. On the contrary, dynamic modelling, is oriented towards understanding the economic structure as well as testing of hypothesis. Nevertheless, it is based on the assumption that most of the economic data series are slow to adjust to any shock and hence to understand the process, one must fully capture the adjustment process which could be complex and tedious. Dynamic modelling makes use of bivariate and multivariate time series analysis. (Asteriou & Hall 2007). A brief description of some of the important terminologies used in time series analysis is given below.

4.5.1 Stochastic Process

This refers to a process, which is a sequence of random variables ordered in time (Gujarati 2003; Kocenda & Cerny 2015). In regression analysis, the dependent variable (Y) is assumed to be stochastic. This means that, it follows a probability distribution. However, the explanatory variables (Xs) are supposed to be fixed or non-stochastic in repeated samples (Brooks 2014). Most of the economic time series data are random. For instance, GDP figures (say $400 bn) for the year 2018 of a country could be the average value of all such possible figures during that year. A normally stochastic process is completely described by the two moments namely mean and variance (Gujarati 2003).

4.5.2 White Noise

White noise is a special type of stochastic process with zero mean, constant variance, and it is serially uncorrelated. Or in other words, it has zero auto correlations with all lags (Brooks 2014). It is also referred to as a purely random process. When a white noise is also independent, then we call it as 'strictly white noise' (Gujarati 2003). In regression analysis, error terms are assumed to be white noise.

4.5.3 Stationary and Nonstationary Time Series

A crucial assumption underlying most of the time series analysis is that it is stationary (Baltagi 2011). According to Gujarati (2003), a time series is considered as stationary "if its mean and variance are constant over time and the value of the covariance between two time periods depends

only on the distance between the two time periods and not the actual time at which the covariance is computed". Some other authors visualize stationarity as a state of statistical equilibrium (Hipel & McLeod 1994). On the other hand, a nonstationary time series, known as an integrated time series is a series with stochastic trend.

4.5.4 Nonstationary Time Series and Order of Integration

If a nonstationary time series becomes stationary after first differencing, it is regarded as integrated of order one, denoted as I (1). If it has to be differenced twice (i.e. difference of difference) to make it stationary, then it is regarded as integrated of order two, denoted as I (2) and so on. Hence, if a nonstationary series has to be differenced 'd' times to make it stationary, it is regarded as integrated of order d, denoted as I (d) (Gujarati 2003).

An I (0) data series is referred as stationary and it oscillates about its average value with constant variance, while an I (1) data series wanders here and there. Hence, it is observed that an I (0) series is mean reverting, whereas an I (1) series is not. An I (1) series can drift away from the mean permanently. This means that, for a stationary time series, any shock that happens at time t has a declining effect as the time pass by and in the end it disappears. On the other hand, for a nonstationary time series the shock will be persistent either with the same magnitude or even lesser (Kocenda & Cerny 2015). As a result, for an I (0) series, the autocorrelations in its correlogram diminish to zero very quickly as the lag order increases, whereas for an I (1) series they decline to zero only very slowly (Gujarati 2003).

4.5.5 Random Walk Model

Random walk model is a classic case of non-stationary time series. As stated by efficient market hypothesis (EMH), stock prices observe a random walk. There are mainly two kinds of random walk. First one being, random walk with drift (constant or intercept term is present) and the other one without drift (i,e no intercept). An important feature of a random walk model is the persistence of random shocks (Gujarati 2011).

4.5.6 Non-Stationarity and Spurious Regression

Stationarity is an essential condition for constructing a time series model for the below mentioned two reasons (Gujarati 2011; Adhikari & Agrawal 2013). Firstly, if a time series is nonstationary, we can study its behavior only for a particular instance. As a result, it is not possible to deduce it to other time periods. Hence, nonstationary time series has no value for forecasting purposes. Secondly, when we have two or more nonstationary time series, regression analysis with such time series may lead to the phenomenon of spurious regression (Gujarati 2003). That is, when a nonstationary time series is regressed with one or more nonstationary time series, we may obtain a high R^2 value and some or all of the estimated coefficients may be statistically significant on the basis of the usual t and F tests. But in reality, there is no true relationship between them because each variable is growing over time. Hence, such tests are not reliable. This is known as the problem of spurious or false regression. Spurious regressions can be verified by checking the low Durbin–Watson d statistic (Gujarati 2003). Another way is looking at the value of R^2 and d. The estimated regression will be spurious if $R^2 >$ d statistic or if $R^2 = 1$ (Granger & Newbold 1974).

4.6 UNIT ROOT TESTS

The commonly used statistical test to ascertain the stationarity of a time series is referred to as 'unit root test' (Shrestha & Bhatta 2018). A review of the three important stationarity test methods, viz. Augmented Dickey Fuller, Phillips Perron and KPSS tests are given below. The null hypothesis of unit root or stationarity is tested against the alternative hypothesis of stationarity in both ADF and PP tests (Paramati & Gupta 2011). On the other hand, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) makes use of the opposite null hypothesis to test for stationarity. i.e here, the null hypothesis is, data is stationary and the alternate hypothesis is, data is nonstationary.

4.6.1 Dickey Fuller Test

Dickey Fuller's tests are based on a simple AR (1) model as given below (Asteriou & Hall 2007)

$y_t = ky_{t-1} + u_t$ ……(1)

Here, it has to be checked whether k=1 (i.e unit root).

The null hypothesis is, H_0: k =1 and alternate hypothesis is, H_1: k<1

Subtracting y_{t-1} from both sides of (1)

$y_t - y_{t-1} = (k-1)y_{t-1} + u_t$

$\Delta y_{t-1} = k_1 y_{t-1} + u_t$ ……. (2)

Now the null hypothesis is, H_0: $k_1 = 0$ and the alternative hypothesis is, H_1: $k_1 < 0$, where if $k_1 = 0$, then y_t follows a pure random walk model.

The presence of a unit root can be tested using two alternate regression equations Dickey and Fuller (1981). The equations are as follows:

$\Delta y_{t-1} = a_0 + k_1 y_{t-1} + u_t$ This equation contains a constant in the random walk process. When $k_1 = 0$, such process exhibit a definite trend in the series, which is generally the case for macroeconomic variables.

$\Delta y_{t-1} = a_0 + a_1 t + k_1 y_{t-1} + u_t$ This equation allows for a non-stochastic time trend in the model.

DF test for stationarity is a normal t test on the coefficient of the lagged dependent variable y_{t-1} from one of the above models. MacKinnon (1996) tabulated appropriate critical values for the above models. If DF the test statistic is lesser than the critical value, then the null hypothesis of unit root is rejected and we can conclude that Y_t is a stationary process.

4.6.2 Augmented Dickey Fuller Test

In order to eliminate autocorrelation, Dickey and Fuller proposed an augmented form of the above test by incorporating more lagged terms of the dependent variable (Asteriou & Hall 2007). The required lag length is decided by Akaike Information Criterion (AIC) or Schwartz Bayesian Criterion (SBC) or by the lag length required to whiten the residuals.

Three possible forms of the ADF test are shown by the equations below.

$\Delta y_t = k_1 y_{t-1} + \sum_{i=1}^{p} b_i \Delta y_{t-i} + u_t$

$\Delta y_t = k_{0+} k_1 y_{t-1} + \sum_{i=1}^{p} b_i \Delta y_{t-i} + u_t$

$\Delta y_t = k_{0+} k_1 y_{t-1} + k_2 t \sum_{i=1}^{p} b_i \Delta y_{t-i} + u_t$

where k_0 is the constant term, k_{2t} is the trend term and u_t is the residual.

ADF test is one of the best methods to check for a unit root when the type of data generating procedure is not known. The critical values of ADF tests are same as that of the DF tests. Both of these tests are based on the assumption that error terms are statistically independent of each other and follow homoscedasticity.

4.6.3 Phillips-Perron Test

Phillips & Perron generalized the procedure for ADF test to propose the Phillips-Perron (PP) test (Perron 1989). The regression test for the Phillips-Perron (PP) test is an AR(1) process:

$\Delta y_{t-1} = k_{0+} k_1 y_{t-1} + e_t$

PP tests make a correction to the t-statistic of the coefficient k_1 from the AR(1) regression to account for the serial correlation in e_t.

Here, the hypothesis is tested for $k_1 = 0$.

The asymptotic distribution of the PP test statistic is similar to that of ADF t statistic and hence MacKinnon (1996) critical values are applicable in this case. PP test make use of nonparametric statistical methods to account for auto correlation in the error terms without adding lagged difference terms (Gujarati 2003). The PP test also can be conducted by including a constant, constant and a linear trend or none of them in the regression. Past studies have reported ADF test to be more reliable than the PP test. Both of these tests face the challenges of size distortion and low power of test (Shrestha & Bhatta 2018). However, PP test is advisable for a larger volume of financial data.

4.6.4 Kwiatkowsky, Phillips, Schmidt and Shin Test

The classical tests for unit root (stationarity) is seen to be biased as it accepts null hypothesis (H_0) most of the time(Shrestha & Bhatta 2018). The test developed by Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) tests stationarity the other way round. The null and alternate hypothesis of this test are as follows:

Null hypothesis (H_0): time series data is stationary

Alternate hypothesis (H_1): time series data is non stationary

The model that is tested using KPSS test is as follows:

$Y_t = X_t + e_t$ where

$X_t = X_{t-1} + u_t$

Now, hypothesis will be tested for the residual u_t. The critical values of KPSS test is adapted from the Lagrange Multiplier (LM) test statistics.

4.7 DIAGNOSTIC TESTS

Diagnostic tests or misspecification tests provide details regarding whether a model has expected statistical properties especially related to the residuals Brooks (2014). Generally, the least square residuals are heteroskedastic with non-zero covariances. These residuals are plotted against the regressors or estimated Y values to identify patterns so that they may indicate nonlinearity, heteroscedasticity and serial correlation Baltagi(2011). According to Gujarati(2011) the regression models try to minimize errors (or residuals). Residual diagnostic tests check whether the error terms are white noise (Shrestha & Bhatta 2018). These tests include Jarque-Bera test for normality, Durbin-Watson and Breusch-Godfrey tests for auto correlation, Breusch-Pagan and Arch LM tests for heteroscedasticity and Ramsey's test for model misspecification. A brief review of these tests are given below.

Jarque and Bera's test for normality assumption is based on the fact that the normal distribution has a skewness value of zero and a kurtosis of value 3. The Durbin Watson (DW) test statistic indicate whether there is first order autocorrelation in the residuals. Here the null hypothesis is that there is no first-order autocorrelation. The absolute value of Durbin–Watson test statistic (d) lies between 0 and 4. If the value of d is near to two, then model is considered to be free from autocorrelation. Durbin-Watson statistic is apt when there is a constant in the regression. However, some authors contend that Durbin Watson test is not suitable for small samples and also for auto regressive models (Gujarati 2003; Asteriou 2007). Breusch–Godfrey test is a Lagrange multiplier (LM) test for higher-order serial correlation with the null hypothesis of no autocorrelation versus the alternative that residuals follow an auto regressive or moving average with a given number of

lags. BG test is a large sample test and is suitable for auto regressive and moving average error series. ARCH test is also another LM test to determine the presence of autoregressive conditional heteroscedasticity for a specified number of lags. It tests for the null hypothesis of no ARCH effect against the presence of ARCH effect. Thus it measures time dependent volatility. Ramsey's RESET test is used to check whether the model has any misspecification by testing whether the model has any omitted variable bias (Baltagi 2011).

4.7.1 Structural Breaks

According to Brooks (2014), a structural break refers to a point from where the characteristics of a time series model show a considerable long-term shift in its behavior. It could be an immediate rise or fall in an economic or financial time series due to the changes in governmental policies, embargo or even external shocks like COVID-19[3]. Structural breaks can occur in intercept, trend or on both (Shrestha & Bhatta 2018). The standard stationarity tests like ADF may fail in the presence of structural breaks as they often tend to reject the null hypothesis of a unit root and thus reporting a time series to be non-stationary, when it is actually stationary (Baltagi, 2011; Brooks 2014). On the contrary, now there are several unit root testing procedures incorporating single and multiple structural breaks (Shrestha & Bhatta 2018). The tests developed by Perron in 1989 and Zivot and Andrews in 1992 are such examples as cited in Kocenda & Cerny (2015).

[3] COVID-19 stands for the recent pandemic Corona Virus Disease 2019.

4.7.2 Stability Tests

These tests are ideally applicable to those models incorporating data over a longer time frame as such models are prone to have structural breaks (Gupta & Goyal 2015). There are several tests for structural breaks. The need to test for a structural break is that estimates obtained from a model would be otherwise meaningless and the implications based on the estimates would be incorrect (Kocenda & Cerny 2015). CUSUM and CUSUMSQ tests by Brown et. al (1975) made use of recursive residuals identify structural changes. Recursive residuals are linear and unbiased residuals which are common in time series regressions. CUSUM test uses cumulative sum of the residuals and tests across the boundary whereas cumulative sum of squares (CUSUMSQ) test is based on plotting the data. Both of these tests do not need to know in advance where the break has occurred (Baltagi 2011). On the contrary, Chow test ascertains if a model has a structural break part-way through on the basis of splitting the data into two, assuming that the break-date is known (Brooks, 2014). The test developed by Vogelsang in 1997 (cited in Kocenda & Cerny 2015) is yet another method which identifies a single break in the trending time series and if so, it enables an estimation of the break date.

4.8 COINTEGRATION

According to Gujarati (2011), co-integration is a situation where the regression of one nonstationary time series with one or more nonstationary time series may not result in a nonsense or spurious regression. But rather, it may cancel out the random or stochastic trends, which could suggest a possible long-run, or equilibrium relationship between them even though individually they are nonstationary. There are various techniques for testing co-integration between variables.

Engle–Granger (EG) tests of co-integration is one among them (Engle & Granger 1987).These are modifications of the Dickey–Fuller (DF) and augmented Dickey–Fuller (ADF) tests. According to Engle and Granger (1987), a regression is run using the two series. Then, their residuals are tested for unit root using Dickey Fuller tests. The idea behind the test is that, if two series are not co-integrated, then a linear combination of the two would be nonstationary including the residuals from the regression (Baltagi 2011). But this method has some limitations. First, the EG two step procedure does not allow for estimation of more than one co-integrating regression. Second, when there are more than two variables, there may be difficulty in identifying the regressand and the regressors. Third, while dealing with multiple time series, there will be challenges to find more than one cointegrating relationship, and also to fit error correction term for each co-integrating relationship (Gujarati 2011).

Johansen test of cointegration is another such method with better statistical properties that deals with multiple time series variables (Johansen & Juselius 1990; Gujarati 2011; Baltagi 2011). Here, the null hypothesis of no or atmost one co-integrating relationship is tested. Under this method, all

the variables to be tested should be of the order 1. Hence it is not applicable with mixed variable models. Lag lengths of the variables selected also will affect the Johansen's test (Brooks, 2014).

ARDL (Autoregressive distributed lag) method is yet another technique used to model the relationship between time series data and predominantly economic variables. This model is popular because of the fact that the co-integration involving nonstationary variables can be constituted as an error correction mechanism and that ARDL method has re-configuration in the error correction form (Kripfganz & Schneider 2016). The bounds testing procedure provides conclusive inference without knowing the order of integration of the variables (Pesaran, Shin & Smith 2001). The optimal lag lengths of the variables can be obtained by either AIC or BIC.

4.8.1 Cointegration And Error Correction Mechanism

Even though, two integrated series are out of equilibrium in the short run, "an equilibrium error term" corrects the deviations of these variables and bring them back to an equilibrium in the long term. This term is called as an error correction term and the mechanism is called as error correction mechanism (ECM). The error correction model was first postulated by Dennis Sargan (Hendry 2003). After extensive research and developments in this field, Engle and Granger postulated the Granger Representation Theorem. According to the theorem, if two variables Y and X are co-integrated, then the association between the two can be written as an error correction model (Gujarati 2003).

4.8.2 Error Correction Models

Consider two variables, Y_t and X_t integrated of order 1 and having a co-integrating relationship between them. Now,

$Y_t = k+bX_t+e_t$ and

$e_t = Y_t -k- bX_t$ which is the co-integrating equation between them.

Now, the error correction model between Y_t and X_t can be written as follows:

$$\Delta Y_t = k_y + a_y e_{t-1} + \sum_{i=1}^{p} a_{1i}\Delta Y_{t-i} + \sum_{i=1}^{p} b_{1i}\Delta X_{t-i} + k_{yt}$$

$$\Delta X_t = k_x + a_x e_{t-1} + \sum_{i=1}^{p} a_{2i}\Delta Y_{t-i} + \sum_{i=1}^{p} b_{2i}\Delta X_{t-i} + k_{xt}$$

where, p denote the lags , k_{yt} and k_{xt} are stationary white noise processes.

k_y and k_x are called the adjustment coefficients of Xt and Yt respectively.

The long run relationship can be explained with the help of the coefficients of the co-integrating equation whereas the coefficients of the error correction model explain how the deviations from the long run affects is getting corrected in the short run (Shrestha & Bhatta 2018).

4.8.3 ARDL Models

An Autoregressive Distributed Lag Models (ARDL) is a dynamic regression model where the features of an autoregressive and distributed lag models are combined (Gujarati 2011). Or in other words, an ARDL model consists of the lagged values of the dependent variable and the current and lagged values of the independent variables.

$Y_t = A_0+A_1Y_{t-1}+\ldots+A_pY_{t-p}+B_0X_t+B_1X_{t-1}+\ldots.+B_qX_{t-q}+u_t$

The above equation can also be written as:

$Y_t = A_0+\sum_{i=1}^{p} A_iY_{t-i}+\sum_{i=1}^{q} B_iX_{t-i}+u_t$

In the above model the lagged Ys constitute the autoregressive part and the lagged Xs constitute the distributed part of the ARDL (p, q) model, for there are p autoregressive terms and q distributed lag terms. A major advantage of an ARDL model is that it not only captures the dynamic effects of the lagged Ys but also those of the lagged Xs. If a sufficient number of lags of both variables are included in the model, residual autocorrelations can be eliminated. The optimal lag orders can be selected by AIC or SIC (Kripfganz & Schneider 2016). These models are generally used for forecasting and also for predicting the multiplier effects of the explanatory variables in the model. The immediate effect, called the impact multiplier, of a unit change in X_t is given by the coefficient B0. For an ARDL (1, 1) model, if the unit change in X_t is sustained, it can be shown that the long-run multiplier is given by:

Long run multiplier = $(B_0+B_1)/(1-A_1)$

if the unit increase in X_t is maintained, the above equation gives the long-run permanent increase in Y_t. The ARDL model makes use of some assumptions. Firstly, the variables Y and X are stationary. Secondly, given the values of regressors, the expected mean value of the error term u_t

is zero. Thirdly, if the error term is serially uncorrelated, then the coefficients of the model estimated by OLS will be statistically consistent (in the statistical sense). However, if the error term is auto correlated, the lagged Y term will also be correlated with the error term, in which case the OLS estimators will be inconsistent. This necessitates the need to check for the autocorrelation in the model by a suitable method. Finally, it is assumed that the X variables are uncorrelated with the error term. The error correction model (ECM) captures the short-run dynamics with the long-run equilibrium.

$Y_t = \alpha + \beta X_t + \delta Z_t + e_t$

The error correction representation of the ARDL model is given as:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \sum_{i=1}^{p} \delta_i X_{t-i} + \sum_{i=1}^{p} \varepsilon_i \Delta Z_{t-i} + \lambda_1 Y_{t-1} + \lambda_2 X_{t-1} + \lambda_3 Z_{t-1} + u_t$$

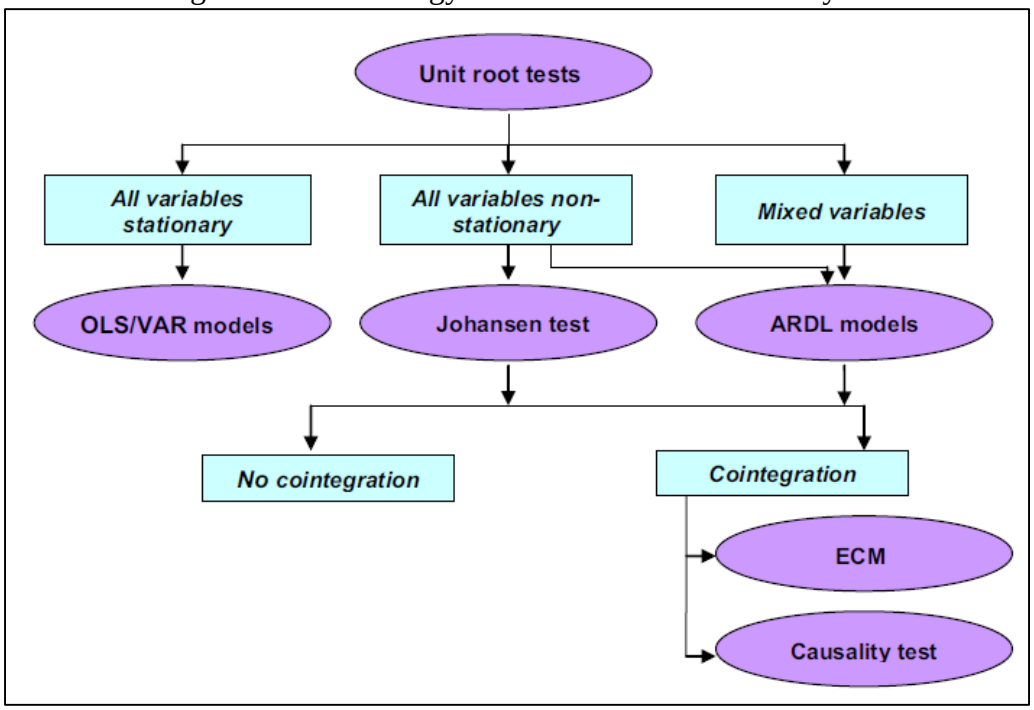
The first part of the above equation indicates short run dynamics of the model while the second part indicates the long-run relationship.

Here the null hypothesis is, H_0: $\lambda 1 = \lambda 2 = \lambda 3 = 0$ (i.e no co-integration) and the alternate hypothesis is, H_1: $\lambda 1 \neq \lambda 2 \neq \lambda 3 \neq 0$ (i.e co-integrating relationship)

4.9 METHOD SELECTION FRAMEWORK

Selecting appropriate models for time series analysis is very important as wrong usage or specification will result in unreliable and biased results(Shrestha & Bhatta 2018). First and foremost, stationarity of the variables has to be checked with unit root tests. If all the variables are stationary, then original least square regression or vector auto regression methods can be employed to get unbiased estimates. On the other hand, if all the variables are non-stationary and are of the same order, Johansen's test can be employed. Furthermore, if the variables under study are mixed, then ARDL method can be used. Moreover, if there is any indication of a long-run linkage between the dependent and explanatory variables, the researcher may use error correction models or causality tests like Granger Causality to further explain the dynamics under data series. This is illustrated in the following figure.

Figure 6: Methodology selection in time series analysis



Source: Adapted from Shrestha & Bhatta 2018, p-6

4.10 MODEL SPECIFICATION FOR COINTEGRATION WITH ARDL

Auto Regressive Distributed Lag (ARDL) co-integration method was used to empirically analyze the long run linkage and dynamic interaction between the explanatory macro variables and the auto indices of the Indian Stock Market (Pesaran, Shin & Smith 2001). This method is employed in this study for the following reasons (Joshi & Giri 2015; Belloumi 2016; Adeleye et al. 2018).

Firstly, compared to other co-integration techniques, bounds testing permits co-integrating relationship to be estimated by a linear regression after the lag length has been specified (Johansen & Juselius 1990). Secondly, unit root testing of the variables is not required under the bounds test. However, this approach requires that all the variables to be integrated of the order I(1). Otherwise, the model cannot be estimated (Perron 1989). On the other hand, ARDL method can be used irrespective of whether the independent variables in the model is I (0) or I (1). But if I (2) series in present, the procedure will crash. Thirdly, for small sample sizes as in the case of this study, this test is more efficient. And finally, the error correction method integrates the short run dynamics with long run equilibrium without losing long run information.

The modified ARDL models constructed to empirically analyze the impact of macroeconomic variables on the movement of the BSE auto index and NiftyAuto index are given below (Joshi & Giri 2015).

Model-1

$$\Delta LBSEAUTO = A_0 + A_1\, LCRUDE_{t-1} + A_2 LER_{t-1} + A_3\, LIIP_{t-1} + A_4\, REPO_{t-1} +$$

$$\sum_{i=1}^{q} a_i \Delta LBSEAUTO_{t-i} + \sum_{i=1}^{q} b_i \Delta\, LCRUDE_{t-i} + \sum_{i=1}^{q} c_i \Delta\, LER_{t-i} +$$

$\sum_{i=1}^{q} d_i \Delta LIIP_{t-i} + \sum_{i=1}^{q} e_i \Delta REPO_{t-i} + \varepsilon_t$ ……..(4.10.1)

Model-2

$\Delta LNiftyAuto = A_0 + A_1 LCRUDE_{t-1} + A_2 LER_{t-1} + A_3 LIIP_{t-1} + A_4 REPO_{t-1} +$

$\sum_{i=1}^{q} a_i \Delta LNiftyAuto_{t-i} + \sum_{i=1}^{q} b_i \Delta LCRUDE_{t-i} + \sum_{i=1}^{q} c_i \Delta LER_{t-i} +$

$\sum_{i=1}^{q} d_i \Delta LIIP_{t-i} + \sum_{i=1}^{q} e_i \Delta REPO_{t-i} + \varepsilon_t$ ……..(4.10.2)

Here, the first part of this equation with A_1, A_2, A_3 and A_4 refer to the long run coefficients and the second part with a_i, b_i, c_i, d_i and e_i refers to the short run coefficients.

The hypotheses are stated as follows:

Null hypothesis Ho: $A_1 = A_2 = A_3 = A_4 = 0$ (i. e No co-integration)

Alternate Hypothesis H1 = $A_1 \neq A_2 \neq A_3 \neq A_4 \neq 0$ (There exists co-integration)

4.11 ARDL BOUNDS TESTING

In the ARDL procedure, the first step is to estimate the above equations (4.10.1 and 4.10.2) by an OLS regression to test the possibility of a long run relationship between the corresponding variables. This is done by conducting an F-test which tests for the joint significance of the lagged levels of variables. After establishing co-integration, the next step is to estimate the conditional ARDL long run model for both the cases (i. e BSEAUTO and NiftyAuto).

The conditional ARDL model for LBSEAUTOt is specified as follows:

$$\Delta LBSEAUTOt = A_0 + \sum_{i=1}^{q} A_1 LBSEAUTO_{t-1} + \sum_{i=1}^{q} A_2 LCRUDE_{t-1}$$

$$+ \sum_{i=1}^{q} A_3 LER_{t-1} + \sum_{i=1}^{q} A_4 LIIP_{t-1} + \sum_{i=1}^{q} A_5 REPO_{t-1} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (4.11.1)$$

Similarly, the conditional ARDL model for LNiftyAuto is specified as follows:

$$\Delta LNiftyAuto_t = A_0 + \sum_{i=1}^{q} A_1 LNiftyAuto_{t-1} + \sum_{i=1}^{q} A_2 LCRUDE_{t-1}$$

$$+ \sum_{i=1}^{q} A_3 LER_{t-1} + \sum_{i=1}^{q} A_4 LIIP_{t-1} + \sum_{i=1}^{q} A_5 REPO_{t-1} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (4.11.2)$$

In the final step, the short run dynamic parameters are estimated by an error correction model with the long run estimates. The error correction version of the above model is as follows:

$$\Delta LBSEAUTOt = const + \sum_{i=1}^{q} a_i \Delta LBSEAUTO_{t-i} + \sum_{i=1}^{q} b_i \Delta LCRUDE_{t-i}$$

$$+ \sum_{i=1}^{q} c_i \Delta LER_{t-i} + \sum_{i=1}^{q} d_i \Delta LIIP_{t-i} + \sum_{i=1}^{q} e_i \Delta REPO_{t-i} + k1\ ECM_{t-1} + \varepsilon_t \ldots\ldots\ldots \quad (4.11.3)$$

$$\Delta LNiftyAuto_t = const + \sum_{i=1}^{q} a_i \Delta LNiftyAuto_{t-i} + \sum_{i=1}^{q} b_i \Delta LCRUDE_{t-i}$$

$$+ \sum_{i=1}^{q} c_i \Delta LER_{t-i} + \sum_{i=1}^{q} d_i \Delta LIIP_{t-i} + \sum_{i=1}^{q} e_i \Delta REPO_{t-i} + k2\ ECM_{t-1} + \varepsilon_t \ldots (4.11.4)$$

a_i , b_i , c_i , d_i and e_i are the short run dynamic coefficients to equilibrium and k_1 and k_2 are the speed adjustment coefficients of LBSEAUTO and LNiftyAuto respectively.

CHAPTER 5: RESULTS

A series of techniques and tests have been employed to analyze the relationship between the finalized macroeconomic variables and the two auto Indices of the Indian stock bourses. Each of these analyses was conducted keeping in mind the properties of time series data. First and foremost, a descriptive statistics of the variables are provided. After plotting the graphs, unit root tests were conducted to confirm the stationarity of the data series. Bounds testing procedure was performed to check for the co-integrating relationship in the data. Following this, ARDL co-integration tests were conducted on both the models under study. Finally, diagnostic tests were conducted for both the models under study to check their robustness as well as stability.

5.1 DESCRIPTIVE STATISTICS

According to Baltagi (2011), it is mandatory to run descriptive statistics on the data as it indicates specific information about the data like outliers, skewness etc. Thus, a descriptive summary of all the variables are provided in the table 5 below. Sample mean, standard deviation, variance, skewness, kurtosis, minimum and maximum values have been reported. The values have been rounded up to three decimal points.

Table 5: Descriptive Statistics of all variables

Variables	Mean	Std. Dev	Variance	Skewness	Kurtosis	Min	Max
LBSEAUTO	9.996	0.146	0.021	-0.788	2.697	9.647	10.194
LNiftyAuto	9.203	0.141	0.020	-0.754	2.769	8.826	9.395
LCrude	4.136	0.148	0.022	-0.159	2.035	3.848	4.388
LER	4.212	0.044	0.002	0.223	1.709	4.153	4.299
LIIP	4.849	0.048	0.002	0.374	3.063	4.765	4.971

LGoldPrice	7.156	0.048	0.002	1.097	4.990	7.083	7.313
LCPI	4.924	0.030	0.001	-0.350	2.267	4.870	4.977
REPO	6.145	0.254	0.064	-0.589	3.684	5.400	6.500

Out of the 32 observations in the sample, the mean value of LBSEAUTO is 9.996 and that of LNiftyAuto is 9.203. The minimum value of LBSEAUTO is 9.647 and the maximum value is 10.194. Similarly, the minimum value of LNiftyAuto is 8.826 and the maximum value is 9.395. There is not much variation in their samples as indicated by the standard deviation/variance values of 0.146 /0.021 and 0.141/ 0.020 respectively. Both are negatively skewed. Kurtosis values are less than 3 and hence it is assumed that the samples have less extreme outliers than a normal distribution (Gupta & Gupta 1986).

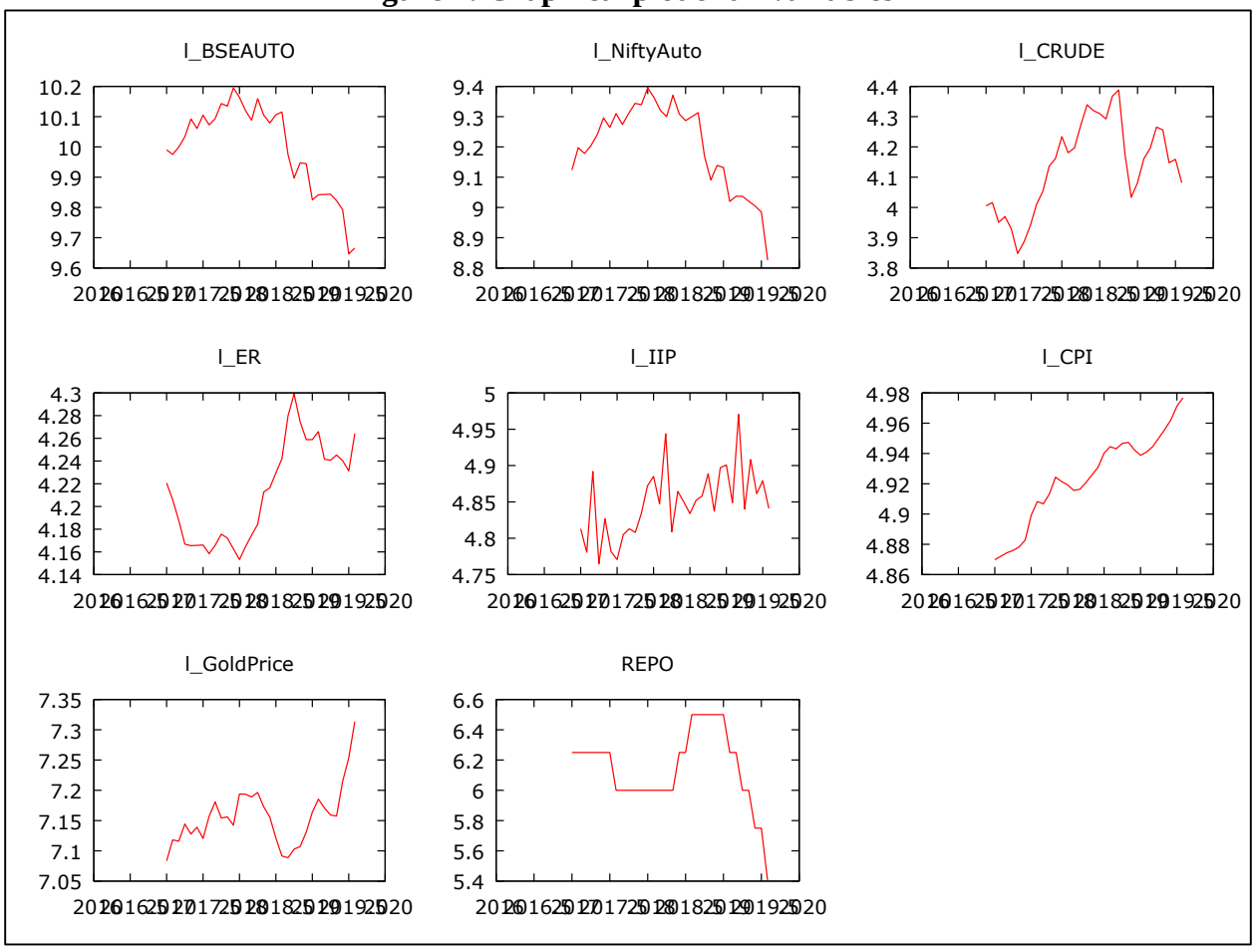
The mean values of LCrude, LER, LIIP, LGoldPrice, LCPI and REPO are 4.136, 4.212, 4.oc849, 7.156, 4.924, 6.145 and the standard deviations are 0.148, 0.044, 0.048, 0.048, 0.030 and 0.254 respectively. The variance and standard deviation values of these variables indicate that there is not much deviation in the sample. Among the explanatory variables, LCrude, LCPI and REPO are negatively skewed where as LER, LIIP and LGoldPrice are positively skewed. The kurtosis figures indicate that LCrude, LER and LCPI are platykurtic while LIIP, LGoldPrice and REPO are mesokurtic (Gupta & Gupta 1986).

5.2 GRAPHICAL ANALYSIS

5.2.1 Log Transformations

Graphical illustration of the variables is the first step in any empirical investigation so as to visualize the time series characteristics. As stated before, it is essential that the variables under study are integrated of order 0 or in other words stationary in order to avoid spurious results. For this study, the natural logarithm of all variables except REPO was taken. A graphical plot of all the initially selected variables viz. BSEAUTO, NiftyAuto, CRUDE, ER, IIP, CPI, GoldPrice and REPO are given below.

Figure 7: Graphical plot of all variables

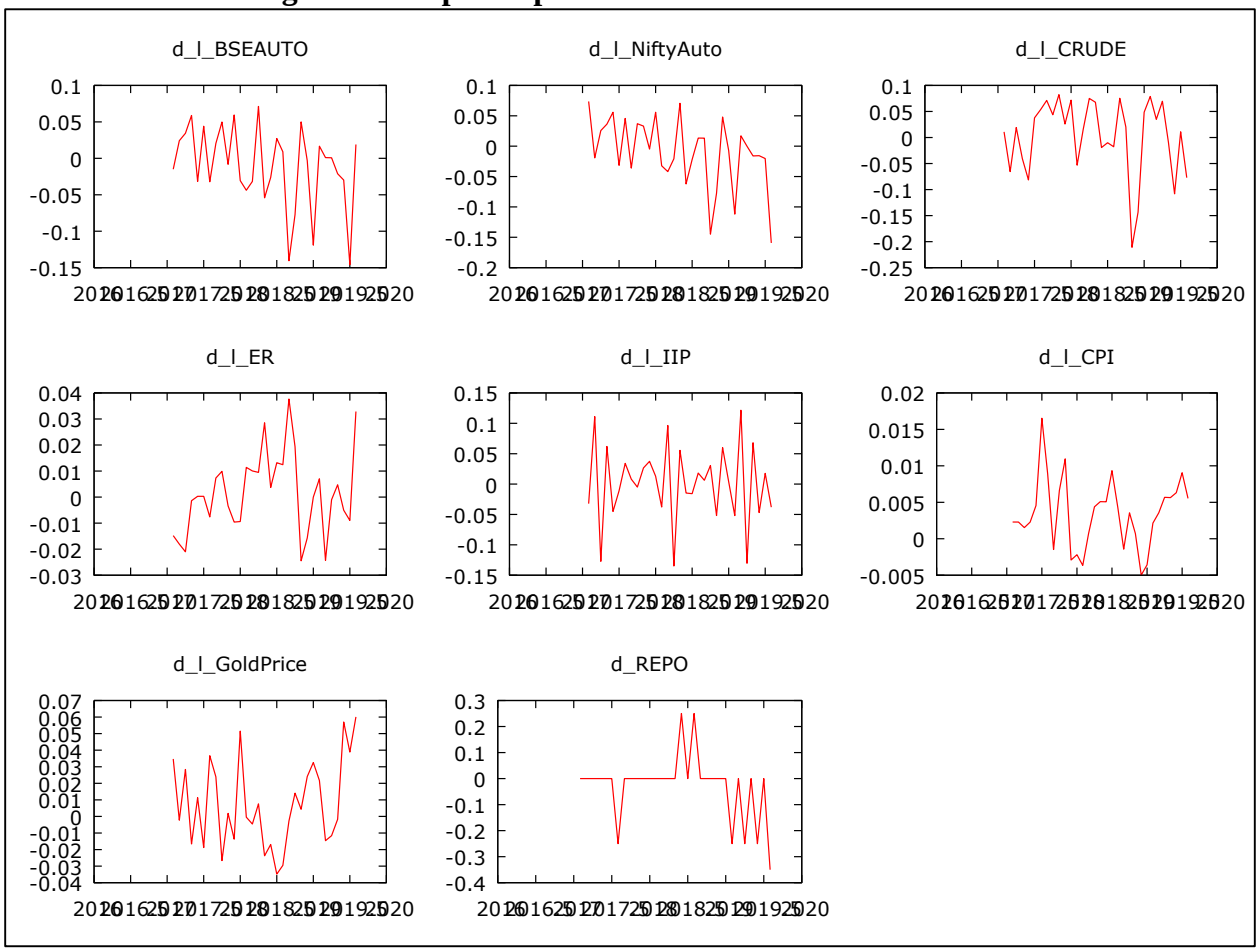


A first look at the above graphs reveals that all variables are trending or in other words non-stationary except LIIP which seems to be stationary around its mean (between 4.8 and 4.85).

5.2.2 First Difference of Log Transformations

As most of the variables are seen to have either clear upward or downward trends, in order to find out the order of integration, first difference of these variables are taken and the graphs are plotted using GRETL. These graphs are shown below.

Figure 8: Graphical plot of first difference of variables



Here we see that all the above variables are stationary around their respective means. Thus all these variables in their first difference forms (i.e d_l_BSEAUTO, d_l_NiftyAuto, d_l_CRUDE, d_l_ER, d_l_IIP, d_l_CPI, d_l_GoldPrice and d_REPO) are integrated of order 0 i.e I(0). Thus we can conclude that, their log forms are integrated of order 1 i.e I(1) . Using the same logic, REPO is also integrated of order 1.

5.3 ADF TEST

ARDL Bounds test is based on the assumption that the variables are of the order 1 or 0. This test fails with variables of order 2 and hence we cannot interpret the F-statistics provided by Pesaran, Shin and Smith (2001). Hence to confirm the order of integration of these variables, unit root test was conducted for all these variables using Augmented Dickey Fuller (ADF) Test and Philips-Perron (PP) Test proposed. These methods test the same null hypothesis and is stated as follows.

H_0: The time series has a unit root (i.e data is non-stationary)

Now if the test statistic is not significant (i.e. absolute value of t-static is lesser than the critical values or in other words if the p-value associated with the test statistic is more than 0.05) then the null hypothesis cannot be rejected.

The results of these tests are provided in the following table.

Table 6: ADF test results

		ADF Test			
	Null Hypothesis	**Test statistic**	**p-value**	**Accept/Reject Decision**	**Test Result**
1	BSEAUTO is not stationary	-1.507	0.8267	Cannot Reject H_0	Variable is non stationary
2	First difference of BSEAUTO is not stationary	-6.545	0.0000	Reject H_0	Variable is stationary
3	NiftyAuto is not stationary	-1.243	0.9014	Cannot Reject H_0	Variable is non stationary
5	First difference of NiftyAuto is not stationary	-6.121	0.0000	Reject H_0	Variable is stationary

5	CRUDE is not stationary	-1.173	0.9159	Cannot Reject H_0	Variable is non stationary
6	First difference of CRUDE is not stationary	-3.905	0.0119	Reject H_0	Variable is stationary
7	REPO is not stationary	0.234	0.9960	Cannot Reject H_0	Variable is non stationary
8	First difference of REPO is not stationary	-5.232	0.0001	Reject H_0	Variable is stationary
9	ER is not stationary	-2.381	0.3895	Cannot Reject H_0	Variable is non stationary
10	First difference of ER is not stationary	-3.531	0.0362	Reject H_0	Variable is stationary
11	IIP is not stationary	-7.039	0.0000	Reject H_0	Variable is stationary
12	First difference of IIP is not stationary	-14.325	0.0000	Reject H_0	Variable is stationary
13	CPI is not stationary	-1.658	0.7689	Cannot Reject H_0	Variable is non stationary
14	First difference of CPI is not stationary	-3.447	0.0454	Reject H_0	Variable is stationary
15	GoldPrice is not stationary	-0.472	0.9845	Cannot Reject H_0	Variable is non stationary
16	First difference of GoldPrice is not stationary	-4.017	0.0083	Reject H_0	Variable is stationary

From the above results it is seen that the log levels of all variables except IIP (LIIP) selected for the study are integrated of order 1. LIIP is integrated of order 0. REPO variable is also used as such in this study and that is of order 1. Hence it is ascertained that there is no problem in going ahead with the ARDL tests.

5.4 PHILIPS-PERRON (PP) TEST

Asterio and Hall (2011) suggests that it is a good idea for the researcher to confirm the order of integration of a series by additionally conducting a PP test. Hence all the above variables were subjected to PP tests as well. The test results are reported in the following table.

Table 7: PP test results

		PP Test			
		Test statistic	**p-value**		**Test Result**
1	BSEAUTO is not stationary	0.671	0.9892	Cannot Reject H_0	Variable is non stationary
2	First difference of BSEAUTO is not stationary	-5.545	0.0000	Reject H_0	Variable is stationary
3	NiftyAuto is not stationary	-0.777	0.9676	Cannot Reject H_0	Variable is non stationary
4	First difference of NiftyAuto is not stationary	-6.644	0.0000	Reject H_0	Variable is stationary
5	CRUDE is not stationary	-1.591	0.4880	Cannot Reject H_0	Variable is non stationary
6	First difference of CRUDE is not stationary	-3.772	0.0032	Reject H_0	Variable is stationary
7	REPO is not stationary	-0.371	0.9148	Cannot Reject H_0	Variable is non stationary
8	First difference of REPO is not stationary	-5.583	0.0000	Reject H_0	Variable is stationary
9	ER is not stationary	-0.902	0.7872	Cannot Reject H_0	Variable is non stationary
10	First difference of ER is not stationary	-3.270	0.0163	Reject H_0	Variable is stationary

11	IIP is not stationary	-5.036	0.0000	Reject H_0	Variable is stationary
12	First difference of IIP is not stationary	-16.431	0.0000	Reject H_0	Variable is stationary
13	CPI is not stationary	-0.614	0.8677	Cannot Reject H_0	Variable is non stationary
14	First difference of CPI is not stationary	-3.443	0.0096	Reject H_0	Variable is stationary
15	GoldPrice is not stationary	-0.708	0.8446	Cannot Reject H_0	Variable is non stationary
16	First difference of GoldPrice is not stationary	-3.925	0.0019	Reject H_0	Variable is stationary

PP test results reported above also indicate that log levels of all variables except IIP (LIIP) selected for the study are integrated of order 1. LIIP is integrated of order 0 and REPO variable is integrated of order 1. Thus PP test also agrees that there is no problem in going further with the ARDL tests. Moreover, the results provided by both the tests (ADF and PP) are consistent.

5.5 MULTI-COLLINEARITY TEST

If there is any linear association between the regressors, it will lead to a problem called multicollinearity (Gujarati 2003). If there is multicollinearity, the estimated regression coefficients are indeterminate and their standard errors are not defined. Hence to avoid this, pair-wise correlations were generated using Stata to be checked. In statistical analysis, correlation is a technique employed to measure the strength of relationship between any two variables. This study makes use of Karl Pearson's correlation. The value of Karl Pearson's correlation coefficient (ϱ) lies between -1 and +1, where -1 indicate a very high negative correlation and +1 suggest a very high positive correlation between the variable. A correlation coefficient value of 0 indicate that the variables under consideration are not related to each other (Levin & Rubin 1998).

Table 8: Correlation matrix

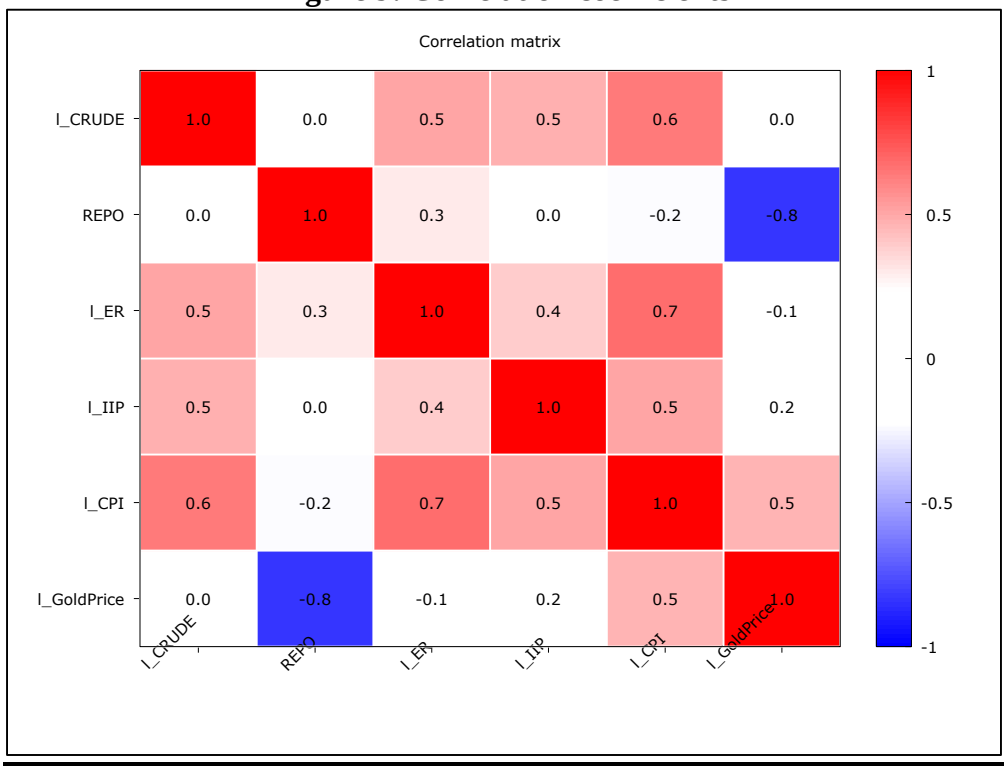
	LBSEAUTO	LNiftyAuto	LCrude	LER	LIIP	LGoldPrice	LCPI	REPO
LBSEAUTO	1.000							
LNiftyAuto	0.930	1.000						
LCrude	-0.063	0.059	1.000					
LER	-0.696	-0.628	0.504*	1.000				
LIIP	-0.329	-0.221	0.472*	0.386*	1.000			
LGoldPrice	-0.426	-0.396	0.033	-0.056	0.176	1.000		
LCPI	-0.577	-0.484	0.632*	0.673*	0.503*	0.458*	1.000	
REPO	0.211	0.246	0.050	0.296	0.030	-0.840*	-0.241	1.000

*Correlations significant at 5% confidence level is starred.

From the above table, it is seen that there is significant and positive correlations between LER and LCrude (50.4 %), LIIP and LCrude (47.2%), LIIP and LER (38.6%), LCPI and LCrude (63.2%), LCPI and LER (67.3%), LCPI and LIIP (50.3%), LCPI and LGoldPrice (45.8%). On the other hand, there is a very high negative correlation (84%) between REPO and LGoldPrice, which is an indication of multi collinearity between the variables. Hence to avoid problems, hereafter LGoldPrice is eliminated from further analysis.

Further, a correlation matrix graph was also generated using Gretl for a better visual analysis.

Figure 9: Correlation coefficients



A visual inspection of this correlation matrix also reinstates a high negative correlation between REPO and LGoldPrice. Thus, LGoldPrice was omitted for subsequent analysis.

5.6 ARDL COINTEGRATION TEST

Having established that the data series under study are a mixed (a combination of I(0) and I(1)) in the previous sections, now we proceed to analyze the co-integrating relationship between the dependent and the finalized explanatory variables using ARDL bounds testing approach (Adeleye et al. 2018). As discussed in the previous sections, an ARDL model can capture both long-run and short-run dynamics of the co-integrated variables. In this method, first the optimal lag length of these variables are selected using AIC criterion. The optimal lag orders have to be selected appropriately so as to ensure that there is no auto correlation in the error terms (Joshi & Giri 2015). Second, bounds test is performed to see if there is a co-integrating relationship between the dependent variables and the explanatory variables. If the bounds testing indicates a co-integrating relationship, the next step is to estimate the long run coefficients using the ARDL test. Then, short run coefficients can be estimated using the ARDL error correction model. But, if there is no indication of a co-integrating relationship from the bounds test, only short run coefficients need to be estimated (Adeleye et al. 2018).

Stata reported a multicollinearity error with LCPI in the model and was automatically eliminated when ARDL regression was done for both models. The step by step ARDL test results for both the models are given separately in the following pages. Moreover, each section also discusses a series of diagnostic tests conducted post estimation to check the robustness and stability of each of these models.

5.6.1 MODEL -1 (DEPENDENT VARIABLE: LBSEAUTO)

5.6.1.1 Lag Length Selection

The next step involves identification of optimal lag orders for the models. For this ARDL regression was run for the dependent and finalized independent variables (LCRUDE, LER, LIIP and REPO) and lag selection was done automatically with the Akike Information Criterion (AIC) method (Arshed 2016) using the following Stata command.

ardl LBSEAUTO LCrude LER LIIP REPO, aic

The optimal lag(s) selected by AIC for the various independent variables while LBSEAUTO is the dependent variable is given below.

Stata command, matrix list e(lags) displays the following output

Variables	**Optimal lag**
LBSEAUTO	**4**
LCRUDE	**2**
LER	**0**
LIIP	**0**
REPO	**2**

5.6.1.2 ARDL Bounds Test

After establishing the optimal lag orders for the different variables, the next step is to identify a possible co-integrating relationship between BSE auto index and the explanatory variables using the ARDL bounds test (Pesaran, Shin & Smith 2001).

Bounds testing procedure gives conclusive inference about the relationship without knowing the order of integration of the variables. This is based on the error correction representation of the ARDL model (Kripfganz & Schneider 2016). The null and alternate hypothesis are as follows.

H_0: No cointegration

H_1: Cointegration

Now, the accept/reject decision is based on three cases. First, if the computed value of F-statistic is more than the critical value of the upper bound of the I(1) regressor, it implies that there is a co-integrating relationship. Hence, the null hypothesis has to be rejected and the long run (error correction) model has to be estimated. Second, if the computed F-statistic is lower than the critical value of the lower bound of the I(0) regressor, null hypothesis will not be rejected. This means that there exists no co-integrating relationship and the short-run model (i.e ARDL) has to be estimated. Last, if the computed F-statistic lies between the lower bound of I(0) and the upper bound of I(1), then the test will be considered inconclusive (Belloumi 2016; Adeleye 2018).

The results from the current study are given below:

Estimated Model: LBSEAUTO = F (LCRUDE, LER, LIIP, REPO)

H_0: no levels relationship

F statistic = 5.943

Regressor	10% crtical value	5% critical value	2.5% critical value	1% critical value
I_1	3.52	4.01	4.49	5.06

Since F statistic > critical value for I(1) regressors, the above null hypothesis is rejected. Hence it implies a co-integrating relationship between the variables.

5.6.1.3 ARDL and ECM Results

Now that a co-integrating relationship has been established, the next step is to estimate the long run as well as the short run dynamics using the ARDL error correction model as specified before (Adeleye et al. 2018).

Table9:ARDL and Error Correction Results for Model-1(ΔLBSEAUTO, ARDL(4,2,0,0,2))

REGRESSORS	**COEFFICIENT**	**t-value**	**p-value**
Constant	13.48718	3.42	0.004
	Long Run Estimates		
LCrude	-.0081605	-0.03	0.980
LER	-4.29146	-3.85	0.002
LIIP	-.3883266	-0.69	0.501
REPO	.2241409	1.88	0.080
	Adjustment (ECM_{t-1})		
LBSEAUTO L1.	-.4715619	-2.46	0.026
	Short Run Estimates		
ΔLBSEAUTO			
LD.	-.403875	-1.97	0.067
L2D.	-.6173856	-3.16	0.006
L3D.	-.4406551	-2.18	0.045
ΔLCrude			
D1.	.014181	0.10	0.924

LD.	.4081337	2.52	0.023
ΔREPO			
D1.	.1416536	1.12	0.280
LD.	.2766853	2.10	0.053
	Regression Statistics		
No. of observations	28		
R^2	0.7274		
Adjusted R^2	0.5094		

Table 9 shows the long run estimates (LR), adjustment (ADJ) or error correction coefficients and the short run estimates (SR) of model-1.

The long run results indicate that crude price (LCRUDE), exchange rate (LER) and index of industrial production (LIIP) have a negative impact on the BSE auto index. At the same time, repo rate (REPO) seems to have a positive influence on the movement of the BSE auto index. However, the coefficient of exchange rate (LER) is only statistically significant (at 1% level) in explaining the variation in the stock index movement. Thus, we can say that exchange rate (LER) is a strong and significant indicator of BSE auto index movement in the long run. This implies that, a 1% increase in exchange rate will lead to a 4.29% decrease in the BSE auto index movement, ceteris paribus. This finding confirms our third hypothesis that, there is a negative association between exchange rate and BSE auto index.

During the time frame taken for this study, the exchange rate of Indian rupee against US dollar was consistently above 64. Despite governmental efforts to build auto supplier industry, India is still a net importer of auto components with high trade deficits (Miglani 2019). As per the data available, for the year 2015-16, this deficit was US$ 13.8bn. Hence, we can say that the depreciation of Indian currency had an adverse impact on the import oriented automotive sector and the same is reflected by the downward spiral of the indices. However, past studies reported positive relationship between exchange rate and stock prices and also between IIP and stock prices (Joshi & Giri 2015). On the other hand, Sinha and Kohli (2015) reported no significant relationship between exchange rates and stock prices where as a negative relationship between interest rate and stock prices was indicated. But, the negative relationship between crude oil price and the index movement is consistent with some other studies (Ahmadian, Hassan & Regassa 2015).

The short-run adjustment process is indicated by the ECM coefficient. The error correction or adjustment term (i.e the first lag of LBSEAUTO) is negative (-0.4715619) and is found to be statistically significant. This figure is an indication of the speed with which the adjustment process is restored to equilibrium following a shock in the long run equilibrium relationship (Adeleye et al. 2018). The speed of adjustment term (ECM_{t-1}) is expected to be negative and its absolute value determines how quickly the equilibrium is restored (Pesaran et al. 1999). In this analysis, ECM_{t-1} = -0.4715619 indicates that 47.16% of the disequilibrium of the previous month's shocks are corrected back to the long run equilibrium in the current month via the explanatory variables.

From the short run coefficients, it is seen that the lagged values of LBSEAUTO and LCRUDE have a significant influence on the auto index and it is significant at 5% level. To be more precise, the second lag (-0.6173856) and third lag (-0.4406551) of BSE auto index are significant at 5%

level. Furthermore, BSE auto index movement in the short run is strongly predicted by the first lag of LCRUDE (0.4081337) and is significant at 5% level. This implies that, in the short run, the movement of BSE auto index is influenced negatively by its own values of the preceding two months and also positively by the crude price of the previous month. This finding rejects our first hypothesis that there is a negative association between crude price and BSE auto index. However, a study conducted by Boldanov, Degiannakis and Filis (2016) posits that amidst different economic as well as geopolitical events, correlations between crude prices and stock indices change. Their study proved that during demand side events like recession, financial crisis, oil shocks and so on, positive correlations were observed between crude price and stock indices across markets. During the last few years, India is also going through slow GDP growth coupled with poor consumer demand, low capacity utilization and crises in the labour market which has led to low risk appetite and low investments. Moreover, demonetization drive in November 2016 and the introduction of goods and services tax (GST) in July 2017 has worsened the economic situation in India. These arguments could possibly justify the other relationships identified in the long run of this model.

Lastly, the value of R^2 =0.7274 shows that 72.74% of the variability in the dependent variable (i.e ΔLBSEAUTO) can be explained by the variations in the explanatory variables (viz. LCRUDE, LER, LIIP and REPO) (Koop 2013).

5.6.1.4 Diagnostic Test Results

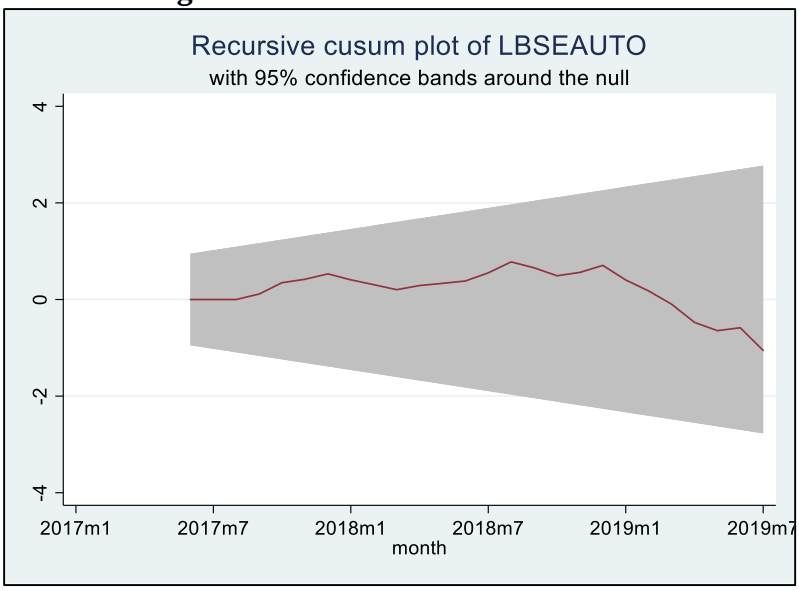
As stated before, diagnostic tests reveal the robustness of estimated regression coefficients (Shrestha & Bhatta 2018). Hence, to validate the strength of the estimated ARDL error correction models in this research study, a few diagnostic and stability tests were conducted. These tests include Jarque-Bera test for normality, Durbin-Watson and Breusch-Godfrey test for auto correlation, Breusch-Pagan and Arch LM tests for heteroscedasticity and conditional heteroscedasticity respectively, Ramsey's test for model misspecification and lastly the CUSUM test for stability (Belloumi 2016 ; Adeleye et. al 2018).

To perform this in Stata, post estimation diagnostics were generated after converting the ardl estimated results to the reg format by writing the command "estimates restore ecreg". This command brings the result of the ardl ecm model in to computer's memory and it will show the results after the "regress" command (Arshed, 2016; Kripfganz & Schneider 2016). The diagnostic test results of the first model with BSE auto index (BSEAUTO) as the dependent variable is discussed below.

Jarque-Bera (JB) test confirmed that the residuals are normally distributed as the null hypothesis of normality cannot be rejected because the test statistic (0.38) was found to be significant at 5% level. The d-statistic from Durbin Watson Test was found to be 2.5, which is close to two. Hence we can say that the residuals are devoid of auto correlation. Breusch-Godfrey LM test for higher-order serial correlation too indicated that the null hypothesis of 'no serial correlation' cannot be rejected at 5% significance level. Breusch-Pagan test revealed that the null hypothesis of 'constant variance' cannot be rejected. Thus, there are no problems of heteroscedasticity in the residuals. Arch LM Test performed to test for the time dependent volatility indicated that there are no auto

regressive conditional heteroscedasticity (arch) effects in the residuals. And finally the regression specification-error test (RESET) for omitted variables revealed that this model does not suffer from omitted values as well Ramsey (1969).The cumulative sum of recursive residuals (CUSUM) test was applied to assess the parameter stability across different sub samples of data (Shrestha & Bhatta 2018). The null hypothesis of this test is that there is no structural break in the data. The test statistic value (0.3617) was within the critical band at 5% level (0.9479) and hence the null hypothesis cannot be rejected. Thus it is concluded that there are no structural breaks in the data. This means that the estimated regression coefficients of the model are quite stable and are reliable (Pesaran, Shin & Smith 2001).

Figure 10: CUSUM Plot for Model-1



The CUSUM plot (see Figure10) also depict that model-1 is robust as the graph lies within the critical bands of 5% significance level of parameter stability. These diagnostic results summarized in Table10 reveal that there are no concerns over normality, auto correlations, heteroscedasticity,

misspecification or structural breaks in the model. Hence the results from the current analysis is reliable for making inferences (Gupta & Goyal 2015).

Table 10: Summary of diagnostic test results for Model-1

	Specification	**Test statistic/p-value**	**Conclusion**
1	JB(normality)	0.38/0.8252	Evidence of normality
2	Durbin-Watson	2.5	No first order auto correlation
3	Breusch-Godfrey	3.459/0.0629	No higher order auto correlation
4	Breusch-Pagan	1.27/ 0.2605	No heteroscedasticity
5	ARCH LM	2.528/0.1118	No conditional heteroscedasticity
6	Ramsey's RESET	0.63/0.6071	No omitted variables
7	CUSUM (recursive)	0.3617/0.9479	No structural breaks

5.6.2 MODEL -2 (DEPENDENT VARIABLE: LNiftyAuto)

5.6.2.1 Lag Length Selection

The optimal lag orders for the second model with Nifty Auto Index (LNiftyAuto) as the dependent variable were selected using the same procedure as discussed before. The Stata command for this step is as follows:

ardl LNiftyAuto LCrude LER LIIP REPO, aic

The optimal lag(s) selected by AIC for the variables while LNiftyAuto is the dependent variable is given below.

Stata command, matrix list e(lags) displays the following output

Variables	**Optimal lag**
LNiftyAuto	**4**
LCRUDE	**4**
LER	**2**
LIIP	**4**
REPO	**1**

5.6.2.2 ARDL Bounds Test

After establishing the optimal lag lengths for the variables, ARDL bounds test was conducted for this model also to check for a possible long run relationship among these variables (Pesaran, Shin & Smith 2001).

Bounds test results are as follows:

Estimated Model: LNiftyAuto = F (LCRUDE, LER, LIIP, REPO)

H_0: no levels relationship

F statistic = 7.036

Regressor	10%	5%	2.5%	1%
I_1	3.52	4.01	4.49	5.06

Since F statistic > critical value for I(1) regressors, the above null hypothesis is rejected. Hence it implies a co-integrating relationship between the variables.

5.6.2.3 ARDL and ECM Results

Table 11: ARDL & Error Correction Results for Model-2 (ΔLNiftyAuto,ARDL(4,4,2,4,1))

REGRESSORS	**COEFFICIENT**	**t-value**	**p-value**
Constant	39.20	3.94	0.004
	Long Run Estimates		
LCrude	0.958	8.26	0.000
LER	-4.3025	-13.84	0.000
LIIP	-2.0583	-4.73	0.001
REPO	0.2461	7.49	0.000
	Adjustment (ECM_{t-1})		
LiftyAuto L1.	-1.2318	-3.47	0.008
	Short Run Estimates		
ΔLiftyAuto			
LD.	-0.0668	-0.37	0.724
L2D.	-0.6318	-2.11	0.068
L3D.	-0.5579	-3.36	0.010
ΔLCrude			
D1.	-0.618	-1.65	0.137
LD.	-0.687	-3.59	0.007
L2D.	-0.154	-0.86	0.413
L3D.	-0.347	-2.09	0.071

ΔLER			
D1	1.815	1.75	0.117
LD	2.226	1.34	0.216
ΔLIIP			
D1.	2.2745	3.34	0.010
LD.	1.6024	2.29	0.051
L2D	0.995	2.29	0.051
L3D	0.394	1.43	0.192
ΔREPO			
D1.	-0.2792	-2.13	0.066
	Regression Statistics		
No. of observations	28		
R^2	0.9465		
Adjusted R^2	0.8195		

Table 11 presents the long run estimates (LR), short run estimates (SR) and the adjustment (ADJ) or error correction coefficients of model-2.

The long run results indicate that ER (-4.3025) and IIP (-2.0583) have a negative impact on the NSE auto index. At the same time, CRUDE (0.958) & REPO (0.2461) seems to have a positive influence on the movement of the NSE auto index. Moreover, the coefficients of all these variables are statistically significant (at 1% level) in explaining the variation in the stock index movement. These findings accept our third hypothesis that there is negative association between exchange rate and Nifty auto index. However, the other three hypotheses are getting rejected. This model reveals that exchange rate is a potential indicator of the Nifty auto index. Moreover, it is very evident that the Nifty auto index also suffer from rupee depreciation in the recent times as most of its listed companies are import oriented. Negative association of IIP with the index along with the positive relationship of the other two regressors viz. crude price and repo rate warrants that things are not right in the Indian economy and in particular, the auto industry.

The error correction or adjustment term (i.e the first lag of LNiftyAuto) in the second model is larger and is negative (-1.2318) and is found to be statistically significant as the p-value (0.008) is less than 0.05. In this analysis, ECMt-1 = -1.2318 indicates that 123.18% of the disequilibrium of the previous month's shocks are corrected back to the long run equilibrium in the present month via the explanatory variables in the model. The coefficient is less than -1 but lies within the dynamically stable range as it is not lower than -2 (Pesaran et al. 1999; Adeleye et al. 2018)

From the short run coefficients, it is seen that ER and IIP has a positive influence whereas CRUDE has a negative influence on the auto index. These results are consistent with past studies (Joshi & Giri 2015; Sinha & Kohli 2015). Moreover, the first lag of CRUDE (-0.687) seems to be a significant predictor of Nifty auto index in the short run. In reality it has got economic significance as well. For the first lag of CRUDE (i,e previous month value), this can be explained as, a 1%

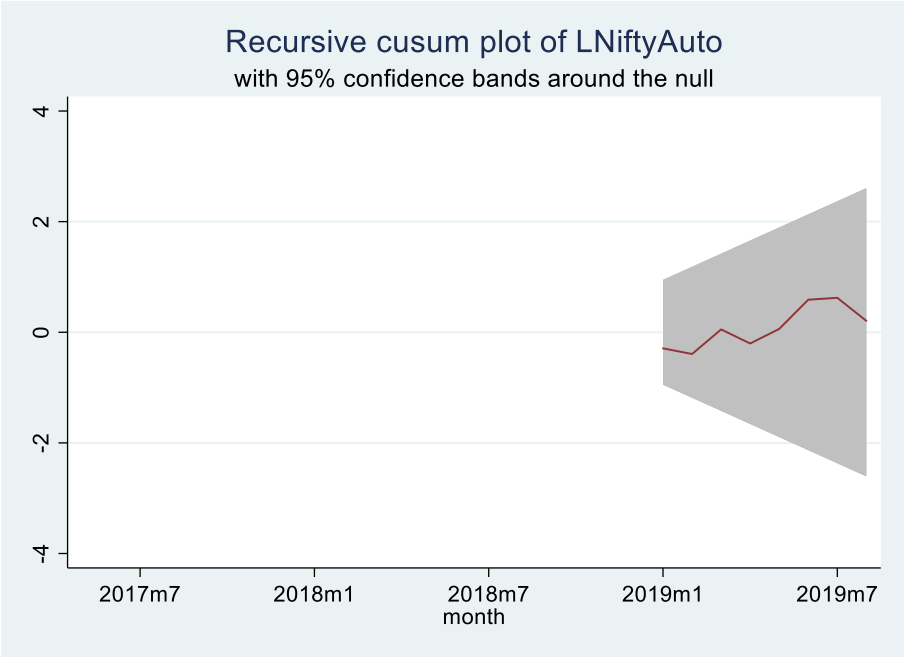
increase of last month's crude price will lead to approximately 0.687% decrease in Nifty auto index in the current month, ceteris paribus. To put it differently, keeping all other things constant, a one unit increase in current month's crude price will lead to 0.687 units decrease in Nifty auto index in the following month. This finding has implications for investors, portfolio managers and policy makers.

The R^2 value = 0.9465 indicates that 94.65% of the variations in Nifty Auto index is explained by the regressors in the model (Koop 2013).

5.6.2.4 Diagnostic Test Results

The sequence of diagnostic tests were repeated in the same order for the residuals of the second model with Nifty auto index (NiftyAuto) as the dependent variable. The test results reported in Table12 indicate that, it passes all the tests except Breusch-Godfrey's test for higher order autocorrelation. Thus there are no problems over normality, heteroscedasticity or omitted variable bias in the model. However, due to the indication of autocorrelation, the estimated regression coefficients will be inconsistent (Gujarati 2003). Conversely, Asteriou and Hall (2007) claims that the coefficients will still be consistent and unbiased but not efficient as consistency and unbiasedness are not based on the autocorrelation assumption. Nevertheless they warn that the variance of the regression coefficients to be biased and inconsistent and thereby making the hypothesis testing invalid. They also argue that the R^2 will be overestimated in these circumstances which is true with our findings for model-2. The CUSUM test for parameter stability reported a test statistic value (0.2620) which was within the critical band at 5% level (0.9479) and hence it is concluded that there are no structural breaks in the data. The CUSUM plot for the model also indicate that the it is stable as the graph lies within the critical bands of 5% significance level of parameter stability. Figure11 shows the CUSUM plot for model-2.

Figure 11: CUSUM Plot for Model-2



The diagnostic and stability tests results of model-2 with NiftyAuto as the dependent variable is given below.

Table 12: Summary of diagnostic test results

Specification	**Test statistic/p-value**	**Conclusion**
JB(normality)	3.87/0.144	Evidence of normality
Durbin-Watson	2.67	No first order autocorrelation
Breusch-Godfrey	6.807/.0091	higher order auto correlation
Breusch-Pagan	0.02/0.8798	No heteroscedasticity
Arch LM	1.488/0.2226	No conditional heteroscedasticity
Ramsey's RESET	1.23/0.3901	No omitted variables
CUSUM(recursive)	0.2620/0.9479	No structural breaks

From the results reported in Table12 above, it is seen that model-2 is robust and stable except for the higher order autocorrelation indication by Breusch-Godfrey test. There could be two reasons for the presence of auto correlations in the model-2 (Gujarati 2003). First, this study used monthly data for which the daily Nifty auto index values were averaged as monthly values of Nifty auto index was not available. This averaging would have smoothened the data and led to systematic pattern within the disturbances and thus introducing autocorrelations. Second, in dynamic regression models like ARDL, the relationship between variables is studied using their growth (first difference) forms. These data transformations from their level forms may also induce autocorrelation. Nevertheless, there are no challenges in estimating the model; yet, the estimated regression coefficients will not be efficient (Gujarti 2003; Asteriou & Hall 2007).

5.6.3 SUMMARY OF RESULTS

ARDL co-integration test on model-1 indicated a statistically significant and negative relationship between exchange rate and BSE auto index in the long run. Similar relationship exists between exchange rate and Nifty auto index too in the long run as indicated by the same test on model-2. Hence, these results confirm our second hypothesis that there is a negative association between exchange rate, BSE auto index and Nifty auto index.

Another noticeable result that emerged from the ARDL analysis of the two models are the values of their short run adjustment coefficients. For model-1 with BSE auto index as the dependent variable, the value is -0.4715619 and for the second model with Nifty auto index as the dependent variable, the value is -1.2318. It can also be seen that, both of these values are negative and

statistically significant as well. Thus we can say that, 47.16% and 123.18% of the disequilibrium of the previous month's shocks are corrected back to the long run equilibrium in the current month via the explanatory variables of BSE auto index and Nifty auto index respectively.

However, the short run estimates of both the models are rather contradictory. The first lag of crude price seems to have a significant positive association with BSE auto index while the former showed a significant negative association with Nifty auto index. Also, when the second and third lags of BSE auto index explain its current movement, only the third lag of Nifty auto index seems to explain its current movement in the short run.

Yet another remarkable result of the analysis is the R^2 values. These values are 0.7274 and 0.9465 for model-1 and model-2 respectively. Thus we can say that, 72.74% of the variations in the BSE auto index and 94.65% of variations in the Nifty auto index can be explained by the variations in their regressors viz. exchange rate, crude price, index of industrial production and repo rate.

CHAPTER 6: CONCLUSION

6.1 Introduction

Macroeconomic variables measure the economic stability of a country. These are factors which cannot be controlled by corporations but might affect the volatility of their stock prices (Mohi-u-Din & Mubasher 2013). The purpose of this study was to examine the relationship between the macroeconomic variables like price of crude, exchange rate, index of industrial production, inflation, repo rate and gold price on the auto indices of the two major Indian stock markets viz. the Bombay Stock Exchange and the National Stock Exchange. All these factors were carefully selected after a thorough review of the literature and also by conducting interviews with experts in the automotive field. Out of the six initially selected variables, inflation and gold price were omitted from subsequent analysis due to the presence of multicollinearity with other variables. Chapter 1 provided an introduction to the topic under study, significance and motivation for undertaking this research, contribution from this study and also the objectives and research questions developed for this study. Chapter 2 provided a detailed discussion on the automotive industry in India, the significance and scope of BSE and NSE and also about their indices. Chapter 3 provides a detailed review of various past empirical studies conducted in similar area. Chapter 4 provides description about the variables used for the study, their sources, the models developed for this study, hypothesis development and also reviews various statistical methods employed for analyzing time series models. Chapter 5 provides the results of various tests conducted. This include a statistical summary of the variables, results of stationarity and collinearity check, bounds test, ARDL co-integration tests and finally the diagnostic test results.

6.2 Implications and Recommendations

Exchange rate turned out to be a strong and statistically significant predictor for both BSE auto index and Nifty auto index in the long run. Additionally, the association was found to be negative. The Indian auto sector comprising the automobiles as well as the auto components, is predominantly involved in export import activities. For example, according to Miglani (2019), India is a lead importer of auto components with very high trade deficits. At the same time, India is one of the major exporters of automotive products across the globe. Hence it is exposed to exchange rate risk. The depreciation of the Indian rupee against the US dollar seem to have an adverse impact on the auto indices of both NSE and BSE during the selected time period. A possible recommendation for corporations to reduce this risk is by adopting appropriate hedging strategies using derivatives (for e.g. currency options, currency futures, currency swaps or foreign exchange forwards).

Furthermore, crude oil price, IIP and repo rates were also found to have a statistically significant relationship with Nifty auto index in the long run. In the short run, first lag of crude was found to have a significant positive association with the BSE auto index and a significant negative association with the Nifty auto index. Many studies have proved significant negative correlation between crude price and stock indices and also between repo rates and stock indices. Auto industry being one of biggest consumers of crude oil, and that too in a country like India, which is one of the biggest importers of crude (Gupta & Goyal 2015), a surge in crude price will result in a dip in auto and allied product sales as the end consumer will have to bear the extra cost of manufacturing and other related services. However, the positive linkage seen could be due to the multiple shocks (demonetization, GST) introduced in to an already slowing down economy which has resulted in poor customer sentiments, low risk appetite and hence, declining investments. Reserve Bank of

India (RBI) uses repo rate as a monetary policy to increase or decrease liquidity in the market. Generally, when repo rate decreases, commercial banks get funds from RBI at a cheaper rate and they will be competing with each other to provide loans to consumers which will eventually influence the stock markets positively. A careful examination of the movement of repo rates between January 2017 and August 2019 indicates that the rates were fluctuating, but was quite low. This has two implications. Either, the commercial banks were not willing to lend money (possibly due to nonperforming asset (NPA) worries) or investors were not interested in parking their funds in auto stocks.

Similarly, conventional wisdom holds that an increase in industrial production will influence the stock prices positively. But the negative association between IIP and the Nifty auto index indicates that, even though there is economic growth, in the long run the current Indian auto industry is not attractive to investors or speculators. Corporations have to see whether the industry is up to date with the market trends and adopt appropriate strategies.

The results from this study has implications for investors, portfolio managers and government too. As some of the macroeconomic factors examined in the present research were found to be statistically significant predictors of auto indices, investors could study the movement of these determinants to understand the possible impact on the auto index before identifying stocks in this sector for parking their funds. In addition, portfolio managers should study similar research reports before finalizing their investment portfolio. Finally, the results of this study could serve as an eye opener for the government and policy makers too. They should watch the current situation of the automotive sector and implement suitable macroeconomic policies to foster growth. This could be in the form of a reduction in tax rate or introduction of scrappage policy in the automotive industry.

6.3 Limitations

Similar to other studies, this study is not free from limitations. This study used a single equation model (BSE auto index / Nifty auto index) for analyzing the association between the dependent variable and explanatory variables in each model. Hence, it is not applicable in those circumstances where there is inter-relationship among the variables. As already discussed in the previous chapter, the second model faces the challenges associated with autocorrelation. Thus the findings from the analysis of the second model is questionable as the model is not efficient. Moreover, there could be problems due to the usage of proxies for the explanatory variables (for example, IIP was used instead of GDP). Another limitation arises from the fact that data used is secondary and hence cannot ward off the problems associated with it. Even more, the finalized four regressors (i.e crude oil price, exchange rate, index of industrial production and repo rate) are not sufficient enough to capture the whole macro economy of India. Furthermore, the time span selected for this study is also small.

6.4 Future Research

Future researchers may incorporate more macroeconomic variables like unemployment rate, foreign direct investment, and foreign institutional investment to have a better outlook on the influence of macro economy on the auto indices. Moreover, they may also consider a longer time frame to extend this study in future. Another interesting idea is to include daily or weekly data for further empirical analyses. Researchers could also incorporate other statistical methods like Granger causality and variance decomposition methods to better understand the dynamics underlying the data. In addition, they can extend this study with simultaneous equation models. Furthermore, they may also incorporate, how other variables like changes in consumer

demography and attitude, changes in government policies (for instance demonetization, introduction of goods and services tax (GST)), proliferation of technology-led disruptive businesses like OLA taxi, uber and the like is impacting the Indian automotive sector. At present, we see a down turn in the automotive industry across the globe. It would be a good idea to identify such global factors which could have an impact on the Indian automotive industry. Additionally, similar studies can be conducted in other countries or a group of countries in a specific region.

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APPENDIX

DIAGNOSTIC TEST RESULTS

Model-1 (DEPENDENT VARIABLE: LBSEAUTO)

1. **Jarque-Bera (JB) test for normality**

H_0: data is normally distributed

Normality test for Model-1

				----------joint ------	
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	Adj chi2(2)	Prob>chi2
residual	28	0.9785	0.5400	0.38	0.8252

Here, the null hypothesis that the data is normally distributed cannot be rejected as the p-value (0.8252) is more than 0.05.

2. **Durbin Watson Test**

The Durbin Watson (DW) test statistic indicate whether there is first order autocorrelation in the residuals. Here the null hypothesis is that there is no first-order autocorrelation. The Durbin–Watson test statistic (d) can take on values between 0 and 4. If the value of d is near to two, then model is considered to be free from autocorrelation. For the current sample, d-statistic was found to be 2.5, which is close to two. Hence we can say that it is devoid of auto correlation. However, Durbin Watson test is not suitable for small samples (Gujarati, 2011).

3. Breusch-Godfrey LM Test

H_0: no serial correlation

Breusch-Godfrey Test for Model-1

lags(p)	chi2	df	Prob > chi2
1	3.459	1	0.0629

The test result indicate that the null hypothesis cannot be rejected at 5% significance level as the p-value (0.0629) is more than 0.05.

4. Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

H_0: Constant variance

Breusch-Pagan test for Model-1

Variables:	fitted values of LBSEAUTO
chi2(1)	1.27
Prob > chi2	0.2605

Since the p-value (0.2605) is greater than 0.05, the null hypothesis of constant variance cannot be rejected.

5. ARCH LM Test

ARCH Test for Model-1

lags(p)	chi2	df	Prob > chi2
1	2.528	1	0.1118

H_0: no ARCH effects vs. H_1: ARCH(p) disturbance

As seen from the table, since the p-value (0.118) is more than 0.05 the null hypothesis cannot be rejected. Hence it is concluded that there is no arch effects in the residuals.

6. Ramsey RESET Test

H_0: model has no omitted variables

F(3, 12) = 0.63

Prob > F = 0.6071

This test does two versions of the Ramsey (1969) regression specification-error test (RESET) for omitted variables. As the p-value (0.6071) is more than the cut off value (.05), this model does not suffer from omitted values.

7. CUSUM Test for stability

Stability Test for Model-1

				LnBSEAUTO
			Number of obs =2	
Statistic	Test Statistic	1% Critical	5% Critical	10% Critical
recursive	0.3617	1.1430	0.9479	0.850

H_0: No structural break

As the test statistic value (0.3617) is less than the critical bands, the null hypothesis cannot be rejected. Hence it is concluded that there is no structural breaks in the data.

Model-2 (DEPENDENT VARIABLE: LNiftyAuto)

1. **Jarque-Bera (JB) test for normality**

Normality test for Model-2

					----------joint ------
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	Adj chi2(2)	Prob>chi2
residual	28	0.2915	0.3541	2.15	0.3409

In this model also, the null hypothesis that the data is normally distributed cannot be rejected as the p-value (0.3409) is more than 0.05.

2. **Durbin Watson Test**

For the current sample, d-statistic was found to be 2.67, which is close to two. Hence we can say that it is devoid of auto correlation.

3. **Breusch-Godfrey LM test**

H_0: no serial correlation

Breusch-Godfrey Test for Model-2

lags(p)	chi2	Df	Prob > chi2
1	6.807	1	0.0091

The test result indicate that the null hypothesis is rejected at 5% significance level as the p-value is 0.0091.

4. **Breusch-Pagan / Cook-Weisberg Test**

H_0: Constant variance

Breusch-Pagan test for Model-2

Variables:	fitted values of NiftyAuto
chi2(1)	0.02
Prob > chi2	0.8798

Since the p-value (0.8798) is greater than 0.05, the null hypothesis of constant variance cannot be rejected.

5. **ARCH LM Test**

ARCH Test for Model-2

lags(p)	chi2	df	Prob > chi2
1	1.488	1	0.2226

As seen from the table, since the p-value (0.2226) is more than 0.05 the null hypothesis cannot be rejected. Hence it is concluded that there are no arch effects in the residuals.

6. **Ramsey RESET test**

H_0: model has no omitted variables

F(3, 5) = 1.23

Prob > F = 0.3901

As the p-value (0.3901) is more than 0.05, this model does not suffer from omitted values bias.

7. CUSUM Test for stability

Table: Stability Test for Model-2

				LnNiftyAuto
			Number of obs = 28	
Statistic	Test Statistic	1% Critical	5% Critical	10% Critical
recursive	0.2620	1.1430	0.9479	0.850

H_0: No structural break

As the test statistic value (0.2620) is less than the critical bands, the null hypothesis cannot be rejected. Hence it is concluded that there are no structural breaks in the data.