FORECASTING THE GLOBAL EXPORT MARKET POTENTIAL OF CERAMIC GLAZED TILE INDUSTRY

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Degree of Master of Science in Business Statistics

Department of Mathematics

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DECLARATION

I declare that this is my own work and this thesis does not in corporate without acknowledgement by any material previously submitted for a Degree or Diploma in any other university or institute of higher learning to the best of my knowledge, and I believe it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. Also, I hereby grant the University of Moratuwa the non-exclusive right to reproduce and distribute my thesis/dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future work (such as articles or books).

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ABSTRACT

In the global business arena, there is an intense competition, both in the world-wide and domestic marketplace. Due to this competition, business bodies of all sizes and varieties have more concern over market movements. It is important to foresee the market rather than arbitrarily competing. When we consider the benchmark of ceramic glazed tile business, it seems that China has managed to grow its market share rapidly in almost every region, and India also seems to be growing their business rapidly. Manufacturing of ceramic glazed tiles is one of the key businesses in Sri Lanka. The main intention of this analysis is to evaluate the ceramic glazed tiles market and develop a model to forecast its potential export opportunities in the coming years. This model of foreseeing the global export potential can help companies in making strategic decisions such as resource level decisions, setting objectives and evaluating performances, investing, exiting from current market, expanding, and venturing into new markets. Based on secondary data extracted from United Nations statistical division for international annual trading, we concluded that the Sri Lankan export market is highly reliant on Australian and North American markets. However, taking construction growth rates and worldwide trading figures into consideration, it is apparent that Sri Lanka has more opportunities in other regions. Based on the VAR model output, it could be concluded that the market will grow by CAGR 6 % (Benchmark 8.3%), 3% (Benchmark 17.1%) and 2% (Benchmark 15.8%) in the Africa, Asia and Middle East regions by 2024 where there are more opportunities. Other than these regions, Oceania, South America and North America are expected to grow by CAGR 10 % (Benchmark 2.8%), 8 % (Benchmark 4.8%) and 0.3 % (Benchmark 20.4%) respectively and there is more opportunity to expand current business in the Oceania region in the coming years.

Key words: ARIMA, Ceramics, Forecast, Multivariate, VAR

DEDICATION

To my wife, baby girl, parents, teachers and spiritual mentors

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LIST OF ABREVATIONS

Abbreviation	Description
AIC	Akaike Information Criterion
ARIMA	Auto Regressive Integration Moving Average
BM	Benchmark
BRICS	Brazil, Russia, India, China and South Africa
CAGR	Compound Annual Growth Rate
EU	Europe
HQ	Hannan Quinn Criterian
HS	Harmonized System
JB	Jarque Bera
ME	Middle East
NA	North America
R&D	Research and Development
SA	South America
SC	Schwarz Information Criterion
SL	Sri Lanka
US$	United States Dollar
UN	United Nations
VAR	Vector Auto Regressive
VEC	Vector Error Correction
WCO	World Customs Organization

CHAPTER 1

INTRODUCTION

1.1 Background

Following the introduction of the open economy in Sri Lanka, the country went through an industrial revolution. Many export-oriented manufacturing industries were established in the country. Some of these industries include apparel, gloves, tires, cosmetics, and fast-moving consumer goods. Among them, the ceramic glazed tiles industry plays a vital role in the national economy. As the country moves forward in terms of development, human necessities and the need for higher living standards also rise parallelly. Thus, new products such as ceramic glazed tiles are being launched worldwide to meet those demands.

1.2 History of Ceramics

Among the ancient industries which remain in the world, ceramics is one of the most significant industries that moved forward with new technology, designs and capabilities. When humans invented that clay can be convert into objects by first mixing it with water and then firing, the pottery industry was born. According to scientists, the processing of clay started around 19000 BC. The oldest finding of pottery in southern Japan is dated between 8000 BC and 9000 BC. As early as 4000 BC fired bricks were used for the construction of temple towers, palaces and walls. More than 2000 years ago the Romans spread the technique of brick making into large parts of Europe. In Egypt, glazed ceramic plates were used as wall decorations for the pyramids in 2600 BC. In China, the art of China porcelain making has been known since 1000 BC. By around 24,000 BC, structures and statues which were made from clay and other materials were, then, fired in kilns which were set up under ground. After 10,000 years from then, more civilized and developed communities came across and tiles were made in civilizations around Mesopotamia. Initially, pottery basins for storing water and clay bricks are thought to be between 9000 or 10,000 BC (ACS, 2014).

1.3 Process of Ceramic Tiles

The term ‘ceramics’ is used for the inorganic materials which made by non-metallic clay compounds for design fixed structures by a firing process. In addition to clay based materials, modern technology ceramics includes a massive amount of products with a small portion of clay or without clay. There are different technologies in ceramic tiles such as glazed, unglazed, porous and vitrified.

Glazed tiles are derived from firing of ceramic bodies induced by time and temperature conversion of the constituent minerals, usually into a blend of new minerals and glassy phases. General properties of ceramic tiles having high strength, wear resistance, chemical inertness, non-toxicity, resistance to heat, fire, electricity, and porosity. The manufacturing process of ceramic takes place in different types of kilns, with a variety of raw materials and in vivid sizes and colours. The processes of manufacturing ceramic products are quite uniform and vary according to manufacturing of wall and floor tiles, household ceramics with numerous stages in the firing process. Usually, minerals are mixed, cast, and pressed into shapes. Bonded and unbounded water molecules regularly used for thorough mixing and shaping. The un-bonded water is evaporated through dryers and bonded water removes in firing chambers known as kiln in higher temperatures. Within the firing curve a very accurate temperature gradient is essential to guarantee the suites of end products. At the end of the process, controlled cooling is crucial, hence products release their heat little by little and preserve their ceramic formation (ISO13006, 1998).

1.4 Classification of Ceramics

There are so many ranges and varieties of product types that can be in the classification of ceramic tiles for floors and walls. The Table 1.1 indicates nine potential classes and the associated product standards. The greater the water absorption of the tile, greater will be its expansion in damp or wet conditions.

Table 1.1: Tiles classification based on water absorption

<table>
<tr><td rowspan="3">Shaping</td><td colspan="4">Water absorption (% by mass, denoted by E)</td></tr>
<tr><td>Group I</td><td>Group IIa</td><td>Group IIb</td><td>Group III</td></tr>
<tr><td>$E \leq 3\%$</td><td>$3\% \leq E \leq 6\%$</td><td>$6\% \leq E < 10\%$</td><td>$E > 10\%$</td></tr>
<tr><td rowspan="2">A – Extruded</td><td rowspan="2">Group AI</td><td>Group AIIa-1</td><td>Group AIIb-1</td><td rowspan="2">Group AIII</td></tr>
<tr><td>Group AIIa-2</td><td>Group AIIb-2</td></tr>
<tr><td rowspan="2">B- Dry Pressed+</td><td>Group Bia $E \leq 0.5\%$</td><td rowspan="2">Group BIIa</td><td rowspan="2">Group BIIb</td><td rowspan="2">Group BIII</td></tr>
<tr><td>Group Bib $0.5\% \leq E \leq 3\%$</td></tr>
<tr><td>C – Tiles made by other processes</td><td>Group CI</td><td>Group CIIa</td><td>Group CIIb</td><td>Group CIII</td></tr>
</table>

Source: ISO 13006:1998(E)

Based on the application, ceramic tiles further can be classified as porcelain, vitrified, semi vitrified, glazed porous and glazed vitrified (Balasubramanian, 2014).

Porcelain (Fully Vitrified):

Porcelain tiles are usually dry pressed. This can be either unglazed or glazed and very low water absorption (less than 0.5%,”B Ia”),

Vitrified and Semi Vitrified:

These tiles can be glazed or unglazed and made by dry pressing or extrusion. These can be separated into two parts based on water absorption. Vitrified tiles Class BIb (dry pressed) and Class AI (extruded) has a level of water absorption of 0.5% to 3%. Semi-vitrified tiles Class BIIa (dry pressed) and AIIa (extruded) has a level of water absorption 3% to 6%.

Glazed Porous Body:

In general, wall tiles have glazed porous bodies with water absorption between 10% and 20% and are classified BIII. When the face of such tiles is covered with a vitreous glazing (either gloss or satin) they are suitable for a wide variety of internal applications. Such tiles are not frost resistant and should only be used in internal conditions above zero temperatures.

Glazed Vitrified:

The porcelain vitrified and semi-vitrified tiles possess similar technical properties when glazed and can be used for internal cladding applications. Only vitrified and porcelain tiles with a water absorption value lower than 3% should be used for external cladding applications in conditions that are subject to frost (Balasubramanian, 2014).

1.5 Global Ceramic Glazed Tile Market

The growth of massive constructions and urbanization has given rise to ceramic tiles significantly across the globe. The value of the worldwide market for ceramic tiles was about US$76.81 billion in 2015. The industry is expected to grow at a CAGR of 9.80% between 2016 and 2024. It is expected that it would reach the value of about US$178.1 billion by 2024 (Vatsavai, 2016).

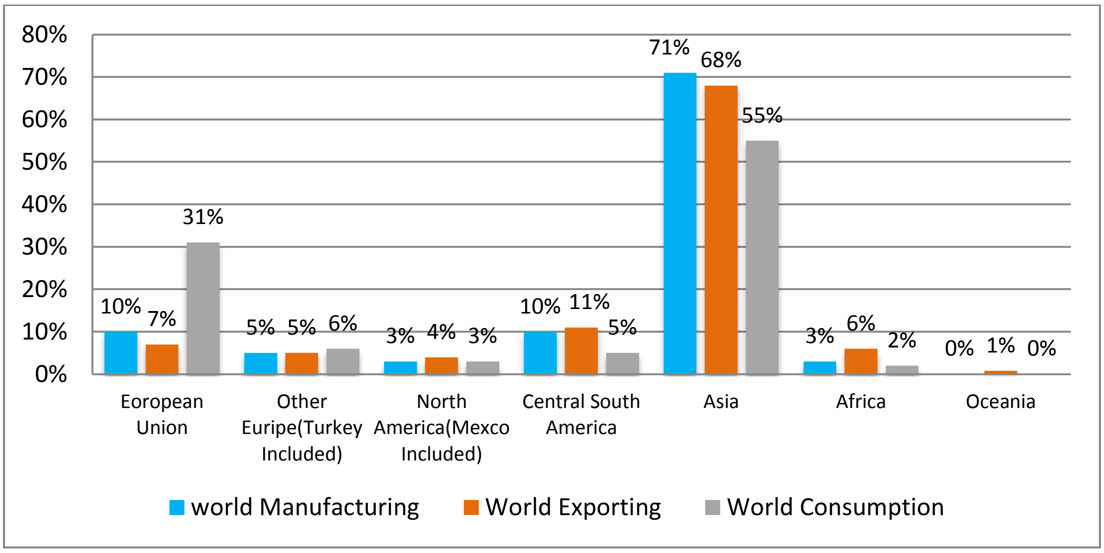


Figure 1.1: Regional ceramic tiles consumption, manufacturing &exports (Source: Vatsavai, 2016)

The worldwide ceramic tiles market has spread across the several continents such as North America, South America, Asia, Europe, Africa and Middle East. A largest consumption of ceramic tiles has been reported in the Asian region according to 2015statistics as per the Figure1.1 and its share was about 65.6% out of overall demand. With the development of Asian countries in areas of infrastructure, urbanization and construction-related activities, especially in emerging economies, countries such as China, India, and South Korea created opportunities for the growth of the ceramic industry during recent history.

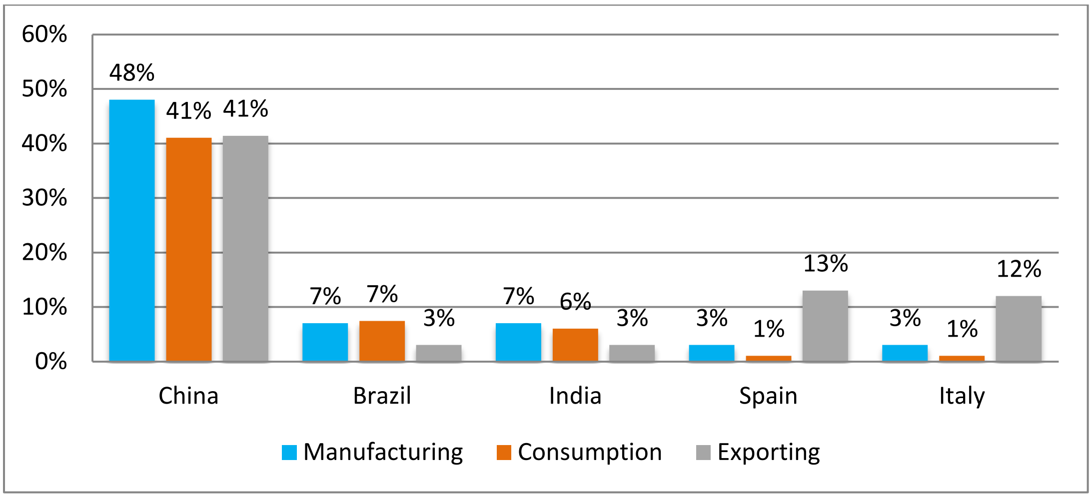


Figure 1.2: Top players in Ceramic Industry (Source:Vatsavai 2016)

According to the Figure 1.2 China is leading with respect to consuming, manufacturing and exporting the ceramic tiles. Irrespective of the market, China seems to be owning a larger proportion of the market share and based on recent ten years back they seems wrapping the global market gradually. Brazil seems to be struggling to keep their market share. According to the recent records, there is a significant improvement in Indian ceramic tile production (Vatsavai, 2016).

1.6 Sri Lankan Glazed Tile Industry

Manufacturing glazed tiles in Sri Lanka was incorporated in 1975 as an export oriented joint venture with Japanese collaboration. Commencing of first commercial production started in May 1977 in Balangoda a manufacturing facility with the involvement of late Prime Minister Mrs. Sirimavo Bandaranaike. The Company executed its first export order in July of the same year in 1978, where 92% of the total output was exported under the Japanese brand name ‘Dento’. At present, there are several companies which engage in both local and export business of ceramic glazed tiles and among them Lanka Wall Tiles, Lanka Tiles and Royal Ceramics are the pioneers (Samanthi, 2017).

1.7 Sri Lankan Ceramic Glazed Tile Industry Challenges

With the increase in global competition, Sri Lanka faces intense competition from cheaper products imported from China, India and other Asian countries. Competitions within Sri Lankan market also become crucial due to cost and margins. Therefore, the Sri Lankan ceramic glazed tiles industry is at a point that needs to focus on cost reduction and boosting the revenue through exports. With the rising competition in the global market, share might be threatened in the coming years. LP gas price fluctuation is another key factor which directly impacts revenue. Uncontrollable price changes in raw materials such as Frits, zirconium silicate and feldspar are another challenge that needs attention. Other than the raw materials, general problems such as overhead costs, political status, inflation, variations in exchange rates corresponding to the dollar and lack of knowledge in information systems are the other challenges that the industry faces. To face these global competitions we need to tackle business in different angles and follow different strategies while using our own strengths to take the industry to the next level. One of key strengths of ours is having a wise workforce compared to other developing countries. This helps in manufacturing the end product to a high quality and retaining good business between the customer and the manufacturer. Following the international standards and obtaining standard industrial certifications is another way of attracting more business to the country. Furthermore, looking for emerging markets in the globe and penetrating deeper into available markets strengthens the industry to a great extent (Samanthi, 2017).

1.8 Markets Needs to be Targeted

Cost has become a key factor that needs to be focused in the current business arena. On one hand, can be targeted to reduce the hidden cost factors and improve productivity. On the other hand we can look at different markets that can be competing. Knowing the customer and their requirement is a crucial factor with respect to managing the cost. According to the Figure1.3, in any population, the largest market proportion is owned by cost-sensitive markets and their quality level is in lower ranges.

Figure 1.3: Markets need to be targeted

Cost and quality-sensitive markets are also known as followers which lie between higher and lower markets. Builders, architects and domestic players are involved in these markets. Their expectations are high compared to cost-sensitive markets. Luxury and up markets can be categorized under the niche category. These markets are governed by Italian and Spanish tiles. These products are unique and exclusive. So we need to address these markets using difference strategies (Vatsavai, 2016).

1.9 Research Objective

The objective of the study is to forecast the export potential of the ceramic glazed tiles industry through forecasting worldwide regional ceramic glazed tiles imports.

1.10 Significance of the Study

The outcome of the analysis would help in making strategic decisions such as resource level decisions, setting objectives and evaluating performances, investing, expanding and venturing into new markets.

CHAPTER 2

LITERATURE REVIEW

This section is devoted to analyzing past research and literature related to the research problem.

2.1 Market Forecast Related to the Ceramic Tile Industry

We have many studies done by various people and research companies around the world related to the ceramic industry. A review of past literature indicates that the ceramic industry seems to be growing in almost every region.

Wintergreen Research cooperation published a study called Ceramics: Market Shares, Strategy, and Forecasts, Worldwide, 2014 to 2020. Through the study they reveal that there has been a significant growth in the ceramic industry. According to their forecasts made in 2014, markets at US$296.2 billion will reach US$502.8 billion by 2020. Growth comes as every industry achieves efficiency in the manufacturing process and using renewable energy. Vendors in the ceramics industry should focus on investing in high-quality production processes and logistics systems that guarantee fast delivery and the development of innovative products in order to increase market share (Lexington, 2014).

The global ceramic tiles market is expected to reach US$ 125.32 billion by 2020, according to the study done through Grand View Research cooperation in 2015. This is due to the construction industry growth in BRICS countries coupled with a rising demand for new residential structures in emerging markets of China and India due to urbanization. Stringent environment regulations pertaining to carbon emissions caused during the production of ceramic tiles has forced market players to increase their R&D expenditure on eco-friendly products, which is likely to open new market avenues in the near future. Residential replacement was the largest application, accounting for more than 50% of market volume in 2013(Kumar, 2015).

The research done by Brooklyn (2016) used different approaches by studying global ceramic tiles market in a segmented manner. She explains the international industry as well as the China, the EU, the US and Japan markets individually. The report examines the global ceramic tiles industry with regard to its history of developments and breakthroughs and the advancements made in technology. The competitive landscape of the global ceramic tiles industry is also understood from the perspective of its key players and major regions. The report also presents the development of major and minor trends in the market global ceramic tiles industry (Brooklyn, 2016).

Inkwood, in 2018 emphasizes that European countries accounted for the second largest ceramic tile consuming nation in the globe in 2017. The Europe ceramic tiles market is expected to grow by CAGR of 8.49% time span over 2018-2026. The bullish construction industry will contribute to this market's expansion. According to the findings, the Russian ceramic tiles market is likely to grow with the highest CAGR. The sporadic fluctuations of raw material prices and the rising contest from low-cost ceramics from the emerging economies may challenge the market in the coming years (Inkwood, 2018).

Transparency market research in 2018 published a research based on the regional ceramic tiles market. The report segregated into North America, Europe, Asia Pacific, Latin America, Middle East and African respect to demand. Asia Pacific was the leading region of the global ceramic tiles market in 2017. Considerable rise in structure and construction actions in this region is the main factor for heavy demand for ceramic tiles. The report analyses and forecasts the market for ceramic tiles at the global and regional levels. The market has been projected in terms of volume and revenue from 2018 to 2026. The study includes drivers and restraints of the global ceramic tiles market. It also covers the anticipated impact of these drivers and restraints on the demand for ceramic tiles during the forecast period. The analysis shows the opportunities for growth business at the global and regional levels. The report comprises detailed analysis, which provides an ample view of the global ceramic tiles market. The study shows market attractiveness analysis, wherein product and application segments have been benchmarked based on their market value, growth rate, and general attractiveness. The study provides a decisive view of the global ceramic tiles market by segmenting it in terms of product, application, and region. These segments have been analysed based on the present and future trends. Regional segmentation includes the current and forecast demand for ceramic tiles in North America, Europe, Asia Pacific, Latin America, and Middle East & Africa (Ahmed, 2018).

2.2 Market Forecast Analysis Done in Similar Industries

Market research for non-metallic products organization has composed an insightful research analysis on the global ceramic matrix composites market, which studies developments shaping demand for ceramic matrix composites. An all-inclusive qualitative forecast has been incorporated in the report that provides an in-depth assessment on driving factors, impeding factors, opportunities and threats impacting growth of the global ceramic matrix composites market. Manufactured by embedding refractory fibres into ceramic matrices, ceramic matrix composites seek enormous applications in various industrial sectors that include energy and environment, aerospace and defence, chemical, and mechanical. Although prospects of the ceramic matrix composites have been promising, growth is limited on the coattails of applications being confined to aforementioned sectors. The global market for ceramic matrix composites has been segmented by the report into end-use industries, product type, and region. The report further studies each segment and offers insights and forecast on these segments for the period between 2017 and 2026 using a comparative analysis (Jamoul, 2018).

According to the market research company called Research for Markets, the global ceramic tube market is accounted for $547.04 million in 2016 and expected to grow at a CAGR of 10.4% to reach $1097.12 million by 2023. The market factors such as demand for power equipment, replacement and refurbishment of existing power infrastructure, stringent environmental norms for circuit breakers are driving the market growth. However, rising energy costs for ceramic manufacturing and volatility of prices are inhibiting the market growth. The increasing share of renewable energy systems will provide ample opportunity for the market to grow. Further, low-cost competition from emerging markets are quite challenging for the market to grow (Sophan, 2019).

Jhonathan Ratner in 1986 published a paper regarding the usefulness of the vector autoregression (VAR) approach to forecasting regional economies. A VAR model and a Bayesian VAR (BVAR) model of selected over several industries in New York for monthly data and their predictions about these variables are compared with ARIMA and transfer function model to forecasts. Overall, the accuracy of BVAR matches or exceeds that of the other techniques. According to his findings BVAR is promising, as a forecasting tool and as a benchmark for regional forecasts (Jhonathan, 1986).

In 1999 Fransisco used VAR and BVAR methodologies as a marketing tool that accomplishes two requirements of forecasting market share and provides insights about the competitive dynamics of the marketplace for the Portuguese car market. The author used to establish that BVAR is a superior forecasting tool compared to univariate ARIMA and VAR models. Because BVAR uses few degrees of freedom and is easy to identify, it satisfies the practical requirements as a marketing forecasting tool. Finally the impulse response and variance decompositions, to illustrate that BVAR provide important insights for the marketing purpose (Fransisco, 1999).

2.3 Summary of Chapter 2

Many researches related to market forecasts in the ceramic industry have been carried out internationally. Most of them have been carried out based on geographical segments. This may be due to expecting that necessity would be similar in the population that live in a particular region. Most of the outcomes of publications have been given by compound annual growth rate considering four to five years ahead using autoregressive models or vector autoregressive models. However, the approaches followed by previous studies were helpful in many ways to conduct ARIMA and VAR forecasting.

CHAPTER 3

MATERIALS AND METHODOLOGY

The data sources and statistical methodologies related to the study have been discussed in this chapter.

3.1 Data Sources

The research is based on the annual imports data from 1997 to 2016 secondary data obtained from the United Nations statistical division commercial trading data base which is known as 'COMTRADE' database. The United Nations Statistics Division is dedicated to developing the global system for statistics. This body disseminates global statistical information, develops standards and norms for statistical purposes and provides supportive information to countries for decision making and helping in national systems in statistics. It acts as a global center for data in international trading, energy requirements, industrial data, environmental, national accounts, social and demographic statistical data which extracted from national and international organizations (United Nations,2003). The Harmonized Commodity Description and Coding System, which is known as Harmonized System (HS) coding is an international standardized system of referring numbers which use in classification of internationally trading product categories. This coding system was introduced by world customs organization in 1988.Earlier this body was known as Customs Co-operation Council and it was an independent intergovernmental organization situated in Brussels, Belgium. Over 200 countries have membership in this organization. In this analysis, the data are extracted under HS code 6908 which described commodity group of Glazed ceramic flags and paving, hearth or wall tiles, glazed ceramic mosaic cubes and the like, whether or not on a backing (World Customs Organisation,1988).

Country wise annual trading figures have been extracted and re-organized in Table 3.1 considering geographical regions.

Table 3.1 : Annual regional ceramic glazed tiles imports in US$

Year	ME	Africa	Asia	NA	Oceania	SA	EU
1997	150,533,486	132,405,380	640,311,112	966,752,503	166,110,109	182,106,267	3,108,689,831
1998	219,138,621	182,874,605	453,823,917	1,156,002,768	173,719,853	197,798,041	3,260,463,491
1999	258,385,528	147,535,609	379,410,072	1,365,229,159	185,403,730	155,466,863	3,097,455,245
2000	360,028,724	163,409,115	407,664,568	1,535,679,193	213,924,666	154,127,243	2,733,726,435
2001	414,918,265	182,837,885	441,045,490	1,597,866,644	162,872,151	134,756,885	2,766,913,311
2002	526,798,232	211,143,194	500,458,644	1,830,261,739	223,819,028	107,990,634	2,936,177,807
2003	704,775,341	239,228,155	572,197,311	2,017,616,133	263,759,235	100,716,240	3,598,367,888
2004	785,784,071	282,298,971	690,789,630	2,277,834,647	293,153,447	138,774,442	4,184,719,226
2005	862,452,583	313,560,285	816,324,468	2,535,477,851	270,257,752	181,479,451	4,284,485,108
2006	982,153,213	477,847,425	1,147,118,353	2,706,989,710	262,066,559	269,672,353	4,588,241,167
2007	1,115,843,881	616,108,653	901,912,350	2,364,686,006	307,756,567	341,814,264	5,463,292,982
2008	1,367,614,175	583,719,487	1,223,958,886	2,015,029,270	319,292,775	493,931,292	5,709,010,026
2009	1,149,095,854	781,945,219	1,033,105,954	1,504,722,349	250,255,224	348,885,292	4,257,204,792
2010	1,366,942,016	995,397,712	1,226,627,988	1,671,993,773	261,390,589	525,302,564	4,143,610,510
2011	1,441,691,797	869,005,042	1,524,561,919	1,686,265,585	241,821,947	620,507,881	4,454,217,500
2012	1,530,354,712	1,048,514,902	1,757,855,012	1,808,900,820	244,370,056	757,310,431	3,876,995,387
2013	1,780,795,077	1,138,145,934	1,834,257,697	2,036,881,068	261,618,926	800,632,954	3,932,432,061
2014	1,969,532,931	1,252,754,635	2,019,845,254	2,149,177,640	304,894,166	615,384,074	4,015,739,240
2015	1,586,897,878	992,134,090	1,924,461,483	2,289,842,688	319,128,726	609,306,572	3,394,271,663
2016	1,792,150,695	945,703,764	1,947,231,066	2,313,780,937	322,298,843	542,607,501	3,503,217,439

Source: https://comtrade.un.org/data/

3.2 ARIMA Time Series Analysis

Autoregressive integrated moving average (ARIMA) model was initiated by Box and Jenkins in 1970. It is a technique which predicts future values of a time series as a linear combination of the error series and own past values. In other words, some people describe it as random shocks or innovations. When the time series shows the non-stationary ARIMA models can be applied to forecasting by making the series stationary by using differencing the initial series (Hamilton, 1994).

3.2.1 Stationarity of the Time Series

To test the stationary of the time series we can simply plot the correlagram and observe the ACF(Auto correlation function) visually and say whether the series is stationary or not. The Augmented Dickey-Fuller (ADF) unit root test is another method which can determines the stationarity of the data. If the initial data series found non-stationarity (non-significance of Augmented Dicky Fuller test) we can try logarithm transformation or differencing the series which may lead to a stationary time series prior to ARIMA. This procedure will be recurrent until the data display no apparent deviations from stationarity which can be describe that series statistical properties such as mean, variance and autocorrelation are not deviating over time. The times of differencing of the data is indicated by the parameter d in the ARIMA(p,d,q) model. Tentatively, differencing of the original series recurrently will eliminate the non-stationarity of the time series (Harvey, 1984).

After converting the data series into a stationary time series, the time series model can be represented as ARMA(p,d,q), which is the blend of auto regressive model of order p and moving average model of order q. Hence, the ARMA(p,q) model can be represent as follows:

$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} + e_t$$

Where

AR (p): $Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p}$

MA (q): $Y_t = \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} + e_t$

3.2.2 Model identification

The ACF(Autocorrelation Function) graph and the PACF (Partial Autocorrelation Function) graph can assist to determine the type and order of the models. If the ACF is in an exponentially declining trend and the PACF contains spikes in the first one or more lags, it suggests that the process best fits the AR models. The number of spikes in the PACF plot can determine the order of the AR terms in the model. If the ACF plot spike in one or few lags later with PACF plot with exponentially declining trend suggests that the process can be described using MA models. The number of significant lags in the ACF plots indicates the order of MA terms. If both ACF and

PACF plots display exponentially declining trend, the model can be described by ARMA type model (Robert, 2005).
After identification of possible models, the best fit model can be described using information criterion techniques for goodness of fit such as Akaike information criterion (*AIC*), Schwarz's Bayesian information criterion (*SC*), and the Hannana-Quinn criterion (*HQIC*)(Harvey, 1997).

Algebraically, these can be representing as follows:

$$AIC = ln(\hat{\sigma}^2) + 2k/T$$

$$SBIC = ln(\hat{\sigma}^2) + k/T$$

$$HQIC = ln(\hat{\sigma}^2) + 2k/T \,.\, ln(ln(T))$$

3.2.3 Model diagnostics

After determining the number of lags in the model, we have to estimate the parameters of the ARMA model. Once the model parameters are estimated, it is necessary to carry on model diagnostics, in order to find the fitted model is adequate. In other words, we need to examine the validity of the fitted model. Firstly, we have to check whether the estimated parameters of the model are significant. Then, it is required to check whether the residuals are white noise, normally distributed and heteroscedasticity available.
The *Q*-statistic can be used to test whether the residuals are white noise. There remains the applied problem of choosing the order of lag to use for the test. If you choose too small a lag, the test may not detect serial correlation at high-order lags. However, if you choose too large a lag, the test may have low power since the significant correlation at one lag may be diluted by insignificant correlations at other lags (Ljung, 1978).

$$Q = T(T+2)\sum_{k=1}^{m} r_k^2/T - k$$

Where: T is the sample size, $r_k$is the sample autocorrelation at lag k and *m* is the lag order

Jarque-Bera test statistic can be used to determine whether the series is normally distributed or not. The test statistically measures the difference between the skewness and kurtosis of the series and with those from the normal distribution (Jarque, 1987).

The statistic can be representing as follows:

$$JB = \frac{N}{6}\,(S^2 + \frac{(K-3)^2}{4})$$

Where :S is Skewness and K is kurtosis

The ARCH test is a Lagrange multiplier (LM) test which use for test autoregressive conditional heteroscedasticity (ARCH) in the residuals. This represents that magnitude of residuals appeared to be related to the magnitude of recent residuals. Testing the ARCH effects may help to improve the efficiency of the model. ARCH test statistic is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH effect order q in the residuals. The regression can be presented as follows:

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s + e_{t-s}^2\right) + v_t$$

Where e denotes the residuals. This is a regression of the squared residuals on a constant and lagged squared residuals up to order q and v_t is regression error term (Engle, 1982).

3.3 VAR/VEC Model

The choice between using a VAR-or a VEC model is based upon the cointegration. After the cointegration test has conducted the choice of model can be established (Lutkepohl, 2007).Johansen's cointegration test is used when variables are found non-stationarity. If variables are non-stationarity then long run relationship needs to be recognized. If two variables are cointegrated, there exists a linear combination between them that are stationary. If cointegration presence VEC (Vector Error Correction) a multivariate approach can be used (Brooks, 2008).

3.3.1 VAR Models

The Vector Autoregression (VAR) model has been introduced by Quenouille (1957) and Sims (1980) who proposed it over economics and became more popular later on. It is one of the popular multivariate time series techniques owing to its flexibility and ease of usage. VAR can be used to hold the mutual influence among multiple time series. The examiner does not require specifying which variables are endogenous and which are exogenous because all are endogenous. Hence, simultaneous equations of structural models can be easily identified as VAR models are rich in structure and that implies that they may be able to capture more features of the data. Also forecasts which are generated by VARs are better than traditional structural models (Lutkepohl, 2007).

A VAR(1) in two variables can be represented in matrix form as below:

$$y_{1t} = \emptyset_{10} + \emptyset_{11}\, y_{1,t-1} + \emptyset_{12}\, y_{2,t-1} + e_{1t}$$
$$y_{2t} = \emptyset_{20} + \emptyset_{21}\, y_{1,t-1} + \emptyset_{22}\, y_{2,t-1} + e_{2t}$$

Based on the first equation $\emptyset_{12}$ denotes the linear dependence of y_{1t} on $y_{2,t-1}$ in the presence of $y_{1,t-1}$.Therefore,$\emptyset_{12}$ is the conditional effect of $y_{2,t-1}$ on y_{1t} given $y_{1,t-1}$. Similar to this second equation also can be explained (Peiris T.S.G, 2016).

3.4 Granger Causality

With multivariate forecasting we need to recognize whether one series causes another series. Suppose there are two series *x* and *y* and by examining how much of the current *y* can be explained by past values of *y* lagged values of *x* and to see whether adding lagged values of *x* can improve the explanation. If so, the *y* is said to be Granger-caused by *x*, if *x* helps in the prediction of *y*, or equivalently if the coefficients on the lagged *x*'s are statistically jointly significant (using the F statistic).If *x* Granger causes *y* or only *y* Granger causes *x*, then it is known as one way causation. If *x* Granger causes *y* and *y* Granger causes *x* is known as two-way causation (Granger, 1969).

CHAPTER 4

FORECASTING OF REGIONAL CERAMIC GLAZED TILES IMPORTS – UNIVARIATE APPROACH

This chapter has been devoted to basic data analysis and univariate forecasting of regional ceramic glazed tiles imports which expected to have high export opportunity.

4.1 Sri Lankan Export Market

In 2016, the total ceramic glazed tile export from Sri Lanka was about 7.6mn square meters worth of US$6.3mn (United Nations, 2003).

Table 4.1: Ceramic glazed tiles exports destinations by Sri Lanka in 2016

Destination	SQM	Trade Value (US$)	Value in %
Australia	533915	3669092	59%
Maldives	80160	845905	14%
USA	37668	845592	14%
Canada	43451	399669	6%
Other(less than 3%)	60106	476694	7%
Total	**755300**	**6236952**	**100%**

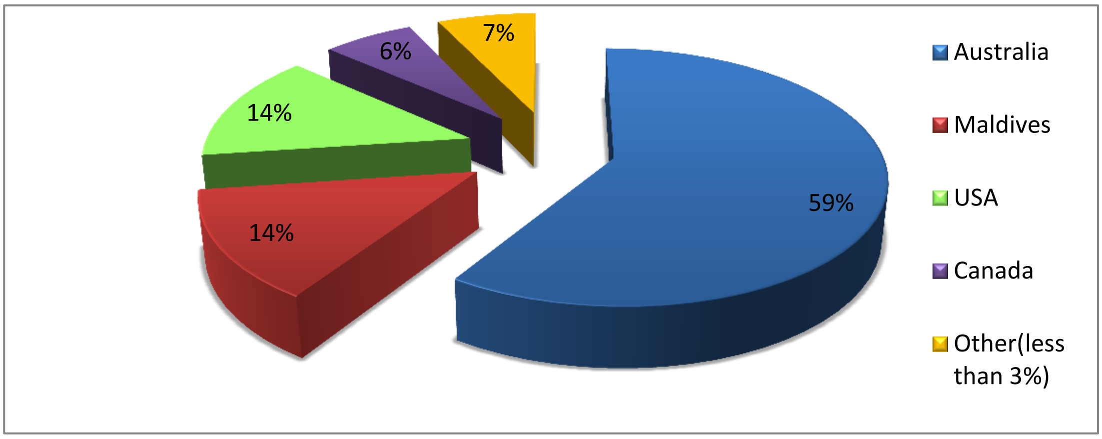


Figure 4.1: Percentage distribution of Ceramic glazed tiles exports from Sri Lanka in 2016

Table 4.1 and Figure 4.1 indicate the share of traded values for each country. It is clear that the largest export destination is Australia which is about 59% of share while Maldives and US carries 14% each.

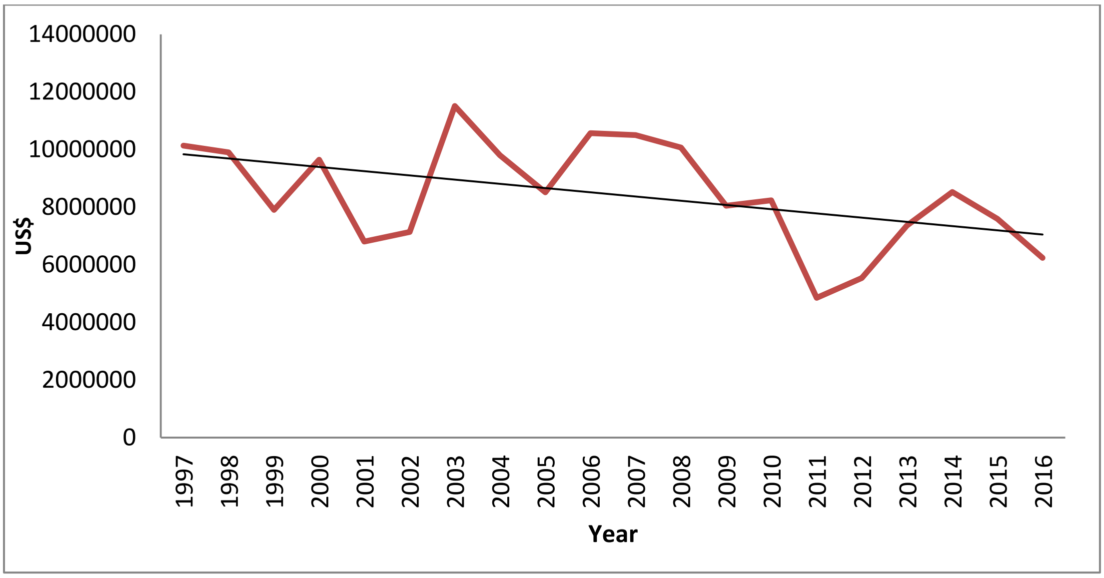


Figure 4.2: Sri Lanka annual glazed tiles exports in US$

Annual exports of Sri Lankan glazed tiles, as per Figure 4.2, does not seem to be having a significant growth according past 20 years figures. It seems to be varying around a flattered line. 2003 shows a highest trading value which is about US$11,504,800 and lowest in 2011 which is US$ 4,855,338.

4.2 Possible Markets to Target

The ceramic tile market is highly related with the construction industry. The highest constructional growth rates are reported in Asia, Africa and ME regions which 7.5%, 6% and 5.5% respectively (Nicolas, 2017). Regional export percentages and construction growth rates have tabulates according to the Table 4.2. Based on the expertise feedback regarding market accessibility, global regions have been categorized in to three possible markets. Though construction growth rates are quite high in the South American region, the market accessibility is quite low due to geographical location and buying power in that particular region. Other than that, the EU market is also quite harder to access and their construction growth rate also seems lowest compared to other regions.

Table 4.2: Sri Lankan exports, construction growth rate and market accessibility

Region	construction growth rate	2012-2016 SL Exp %	Market Accessibility	Trading Opportunity
Asia	**7.50%**	**17.50%**	Moderate	High
Africa	**6.00%**	0.90%	Moderate	High
ME	**5.50%**	0.20%	Moderate	High
Oceania	5.00%	**56.40%**	Moderate	Medium
SA	5.00%	0.00%	Low	Low
NA	4.30%	**24.10%**	Moderate	Medium
EU	2.00%	0.90%	Low	Low

Based on basic findings, worldwide regions can be classified in to three areas as high opportunity, moderate opportunity and low opportunity markets as per the Figure 4.3. High opportunity markets are expected to have high business growth, ease of market accessibility and insufficient penetration according to the current Sri Lankan export figures.

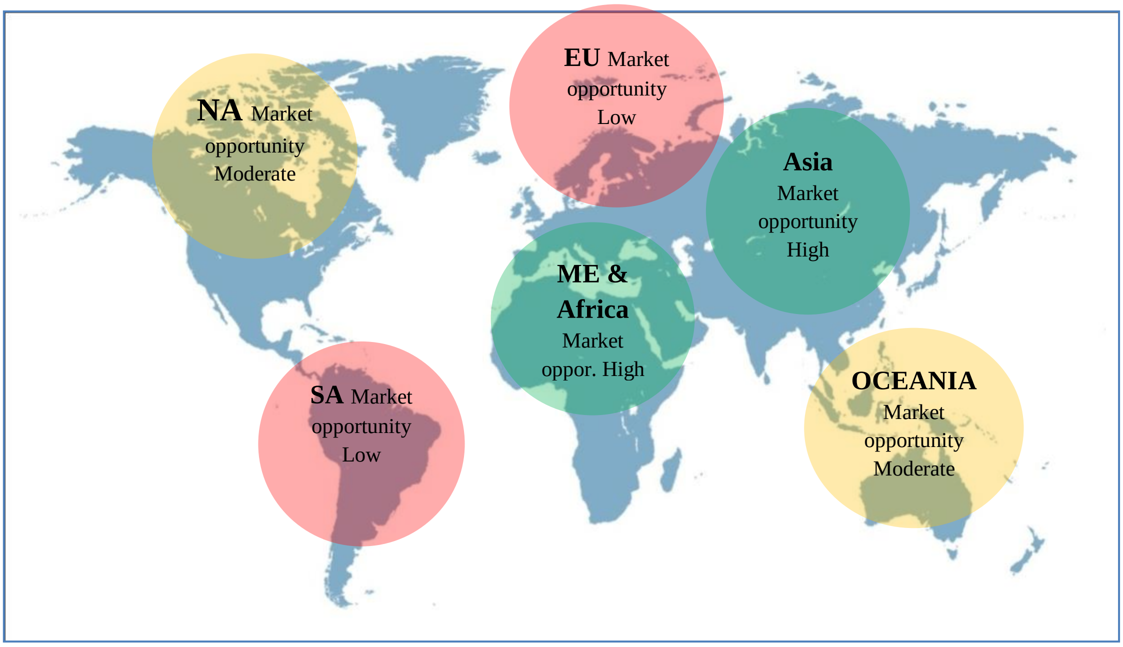


Figure 4.3: Region wise expected markets

4.3 Temporal Variability of Regional Imports

Based on the raw data of regional imports, plotted the time series graphs to observe the movement of individual regional performances. To observe the nature of imports (in US$) over the time, temporal variability of original geographical series has been plotted from 1997 to 2016 according to Figure 4.4.

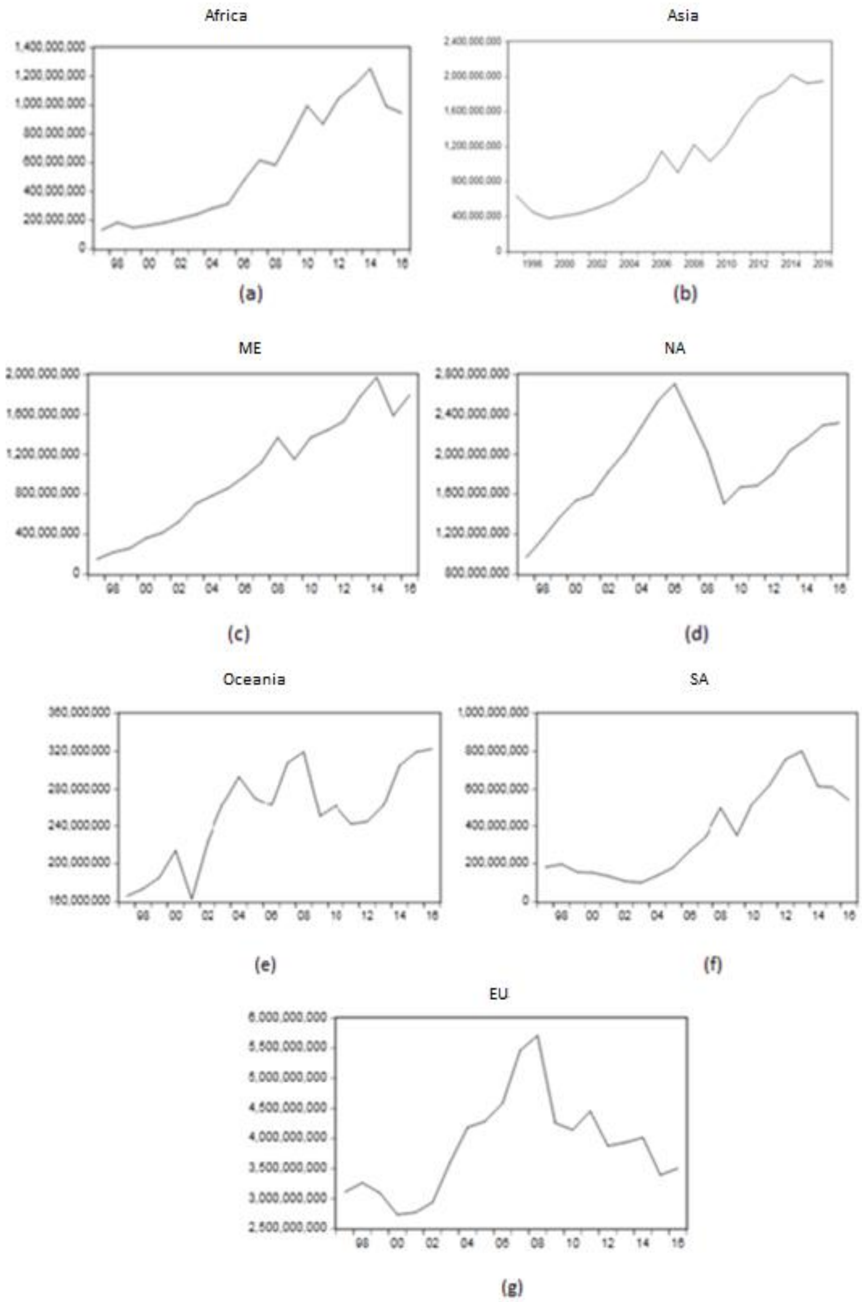


Figure 4.4: Temporal variability of geographical regional imports.(a) Africa, (b) Asia, (c) ME, (d) NA,(e) Oceania, (f) SA, (g) EU

Except the EU region, all the other regions are showing an increasing trend. It appears that the economic crisis in 2000 affected almost all the regions except ME and Africa. Irrespective of region, economic crisis in 2008 has affected all the regions and figures shows the rapid decrement in NA, EU and Oceania. When compared on each other ME, African and Asian regions shows a rapid upward trend and there may be a good opportunity in the market place. When compared to SL exports records, it seems that we were unable to penetrate enough in to these three markets. So further investigate in these three regions univariate time series approach has used.

4.4 Forecasting Imports of Ceramic Glazed Tiles by ME Region

Imports of glazed ceramic tiles (in US$) for ME region varies between $1.51*10^8$ (min) and $1.97*10^9$(max) with the mean of $1.02*10^9$ according to the Table 4.3.The data seems negatively skewed (Skewness 0.0067). Also JB=1.33 test and *p* value is not significant (p = 0.51). The original series variation is quite larger. Thus original series has converted to logarithmic series.

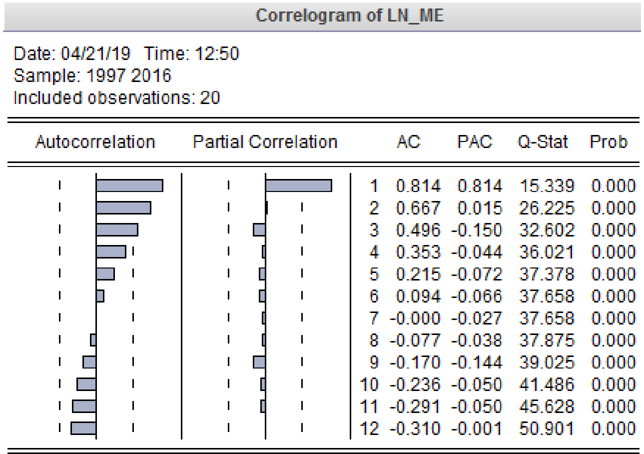
Table 4.3: Descriptive Statistics of ME original series&log converted series

	Mean	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Jarque-Bera**	**Prob**
ME	1.02E+09	1.97E+09	1.51E+08	5.76E+08	-0.00673	1.33230	0.51368
LN_ME	20.51834	21.40106	18.8297	0.767792	-0.80971	2.41440	0.29903

Log converted series varies between 18.82 (min) and 21.40(max) with the mean of 20.51 according to the Table 4.3 and data seems negatively skewed (skewness 0.809). Also JB=2.41 test and *p* value is not significant (p = 0.299).

4.4.1 Stationarity of ME Log Converted Series

Stationarity of series is very desirable factor and this can be recognized through the correlagram of the series.



Correlogram of LN_ME

Date: 04/21/19 Time: 12:50
Sample: 1997 2016
Included observations: 20

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.814	0.814	15.339	0.000
		2	0.667	0.015	26.225	0.000
		3	0.496	-0.150	32.602	0.000
		4	0.353	-0.044	36.021	0.000
		5	0.215	-0.072	37.378	0.000
		6	0.094	-0.066	37.658	0.000
		7	-0.000	-0.027	37.658	0.000
		8	-0.077	-0.038	37.875	0.000
		9	-0.170	-0.144	39.025	0.000
		10	-0.236	-0.050	41.486	0.000
		11	-0.291	-0.050	45.628	0.000
		12	-0.310	-0.001	50.901	0.000

Figure 4.5: Correlagram of level ME Log converted series

Augmented Dickey-Fuller Unit Root Test on LN_ME

Null Hypothesis: LN_ME has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	3.749137	0.9997

Figure 4.6: Augmented Dickey Fuller test of level for ME region

Correlagram (Figure 4.5) and ADF test (Figure 4.6) of the log converted series for ME region emphasize that the series is not stationary at the level.

Null Hypothesis: D(LN_ME) has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.670028	0.0887

(a)

Null Hypothesis: D(LN_ME,2) has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-5.602204	0.0000

(b)

Figure 4.7: Augmented Dickey Fuller test for ME region: (a) 1st difference (b) 2nd difference

Retested the series using ADF test for 1st difference, according to the Figure 4.7(a) and 2nd difference according to the Figure 4.7(b) of logarithmic series. The ADF results presented in Figure 4.7(b) confirms that 2nd difference of logarithmic transformation series is stationary at 5% significance level (p=0.000).

4.4.2 Model Identification and Parameters Estimation

Observing the ACF plots and PACF plots of the stationary series can be used to tentatively recognize the order of autoregressive or moving average terms (Robert, 2005). As shown in ACF and PACF plot in Figure 4.8 the first spike and in PACF first and second lag has cut off the boundaries. According to ACF, process may fit MA(1) type model and PACF suggest that process may fit AR(1) or AR(2) type model.

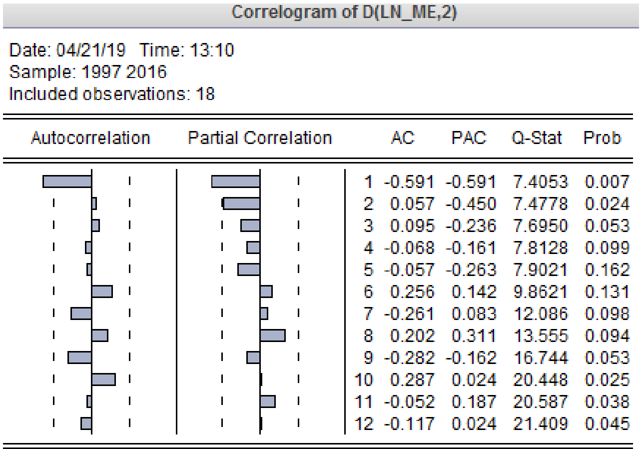


Figure 4.8: ACF/PACF Log converted 2nd Difference (ME imports)

Observing ACF and PACF of differenced model, following models were tested:

Table 4.4: Comparison of Univariate models for ME region

Model	Model coefficients	AIC	SC
ARIMA(0,2,1)	Not significant	1.019	0.8706
ARIMA(1,2,1)	Not significant	1.1682	0.9703
ARIMA(2,2,1)	Not significant	1.1126	0.8653
ARIMA(1,2,0)	Significant	0.7122	0.5638
ARIMA(2,2,0)	only AR(1) significant	0.9013	0.7034

As per the comparison of univariate models which are shown in Table 4.4 the significance of model coefficients and lower information criterion values suggest that the ARIMA (1,2,0) model is better among all tested models.

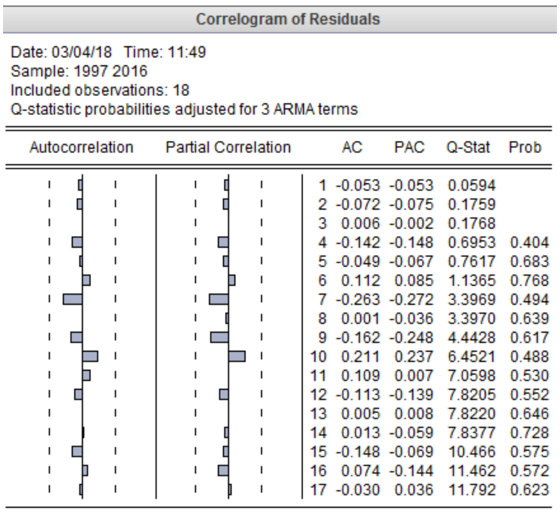
Table 4.5: Univariate model for ME region

Model	Model Coefficients and Adequateness				
Model 1 : ARIMA (1,2,0)	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	C	-0.017905	0.027187	-0.658573	0.5202
	AR(1)	-0.725457	0.216636	-3.348739	0.0044
	SIGMASQ	0.019744	0.009107	2.167923	0.0467
EViews Equation d(lN_ME,2) c ar(1)	R-squared	0.462178	Mean dependent var	-0.014105	
	Adjusted R-squared	0.390468	S.D. dependent var	0.197154	
	S.E. of regression	0.153923	Akaike info criterion	-0.712206	
	Sum squared resid	0.355385	Schwarz criterion	-0.563810	
	Log likelihood	9.409850	Hannan-Quinn criter.	-0.691744	
	F-statistic	6.445132	Durbin-Watson stat	2.589356	
	Prob(F-statistic)	0.009545			

As shown in Table 4.5 model ARIMA(1,2,0) adequate (F= 6.44,p=0.009) and lower information criterion techniques(AIC 0.7122) and (SC 0.5638) indicates model fits appropriately.

4.4.3 Residual Diagnostics

Residual diagnostic is other important test to validating the model.


Correlogram of Residuals

Date: 03/04/18 Time: 11:49
Sample: 1997 2016
Included observations: 18
Q-statistic probabilities adjusted for 3 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.053	-0.053	0.0594	
		2	-0.072	-0.075	0.1759	
		3	0.006	-0.002	0.1768	
		4	-0.142	-0.148	0.6953	0.404
		5	-0.049	-0.067	0.7617	0.683
		6	0.112	0.085	1.1365	0.768
		7	-0.263	-0.272	3.3969	0.494
		8	0.001	-0.036	3.3970	0.639
		9	-0.162	-0.248	4.4428	0.617
		10	0.211	0.237	6.4521	0.488
		11	0.109	0.007	7.0598	0.530
		12	-0.113	-0.139	7.8205	0.552
		13	0.005	0.008	7.8220	0.646
		14	0.013	-0.059	7.8377	0.728
		15	-0.148	-0.069	10.466	0.575
		16	0.074	-0.144	11.462	0.572
		17	-0.030	0.036	11.792	0.623

Figure 4.9: Correlagram of residuals for ARIMA 1,2,0 model ME region

As shown in Figure 4.9 correlogram of the residuals confirm the white noise of residuals.

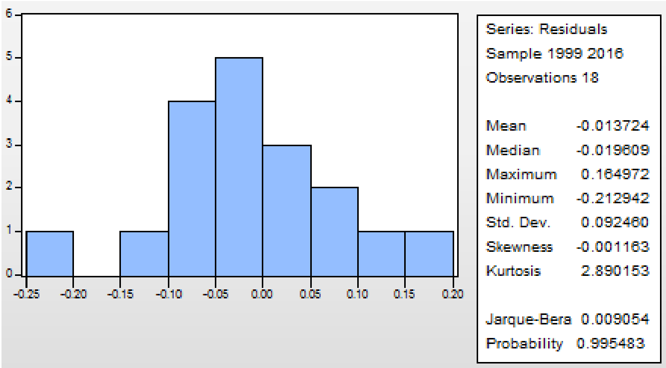


Figure 4.10: JB Test for residuals for ARIMA 1,2,0 model ME

According to the Figure 4.10 JB test is not significant (p=0.99) and it confirms that the residuals are normally distributed.

Heteroskedasticity Test: ARCH

F-statistic	0.010384	Prob. F(1,15)	0.9202
Obs*R-squared	0.011760	Prob. Chi-Square(1)	0.9136

Figure 4.11: Heteroskedasticity test for ARIMA 1,2,0 model ME region

Figure 4.11 illustrates the results for testing heteroscedasticity of the residuals. Non significance of the test (observed R-squared 0.0117, p 0.9136) reveals that there is no ARCH effect.

4.4.4 Fitted Model for ME Region Glazed Tiles Imports

Based on the above outcome ARIMA(1,2,0) model can be recommend to forecast the export potential of ceramic glazed tiles to ME region. A derived model can represent as below.

ARIMA (1, 2, 0)

Y”= $\mu + \phi 1$ Y”$_{t-1} + e_t$; Where Y”= [Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)]

Y”= -0.018 - 0.725 Y''_{t-1} + 0.02 ; Where Y”= [Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)]

[Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)] = -0.018 -0.725[Y (t-1) –Y (t-2)] -[Y (t-2) – Y (t-3)] + 0.02

Y(t) = 1.275Y(t-1) +0.45Y(t-2) -0.725Y(t-3) + 0.002

Here Y(t) is log converted series (Y(t) =lnX(t))

lnX(t) = 1.275lnX(t-1) +0.45lnX(t-2) -0.725lnX(t-3) + 0.002

4.5 Forecasting Imports of Ceramic Glazed Tiles by African Region

An African import of glazed ceramic tiles varies between $1.32*10^8$ (min) and $1.25*10^9$(max) with the mean of $5.78*10^8$. The data seems positively skewed (Skewness 0.29). Also JB=2.07 test and *p* value is not significant (p = 0.35) as per Table 4.6. The standard deviation is ($3.9*10^8$). Thus original series variation is quite larger, original series has converted to logarithmic series.

Table 4.6: Descriptive statistics of African region original and log converted series

	Mean	Max	Min	Std. Dev.	Skewness	Jarque-Bera	Prob
AFRICA	5.78E+08	1.25E+09	1.32E+08	3.90E+08	0.291073	2.073385	0.354626
LN_AFRICA	19.90482	20.94861	18.70138	0.796053	-0.15493	2.157064	0.340094

The log converted series varies between 18.70 (min) and 20.94(max) with the mean of 19.90. Data seems negatively skewed (Skewness 0.15). Also JB=2.15 test and *p* value is not significant (*p* = 0.34) as per Table 4.6.

4.5.1 Stationarity of Log Converted African Series

Stationarity of series is a very desirable factor and this can be recognized through the correlagram of the series.

Correlogram of LN_AFRICA

Date: 04/21/19 Time: 23:19
Sample: 1997 2016
Included observations: 20

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.884	0.884	18.097	0.000
		2	0.786	0.020	33.189	0.000
		3	0.635	-0.291	43.619	0.000
		4	0.471	-0.194	49.728	0.000
		5	0.300	-0.120	52.373	0.000
		6	0.145	-0.028	53.030	0.000
		7	-0.021	-0.161	53.046	0.000
		8	-0.163	-0.086	54.022	0.000
		9	-0.288	-0.058	57.347	0.000
		10	-0.380	-0.010	63.715	0.000
		11	-0.426	0.083	72.581	0.000
		12	-0.452	-0.053	83.842	0.000

Figure 4.12: Correlagram of level(Log converted African region imports)

Augmented Dickey-Fuller Unit Root Test on LN_AFRICA

Null Hypothesis: LN_AFRICA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.254103	0.6281

Figure 4.13: Augmented DF test(Log converted African region imports)

According to the correlagram (Figure 4.12) and ADF test (Figure 4.13) log converted African series of level is not significant (p=0.628). It confirms that the original series is not stationary.

Null Hypothesis: D(LN_AFRICA) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.433212	0.0929

(a)

Null Hypothesis: D(LN_AFRICA,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.363045	0.0006

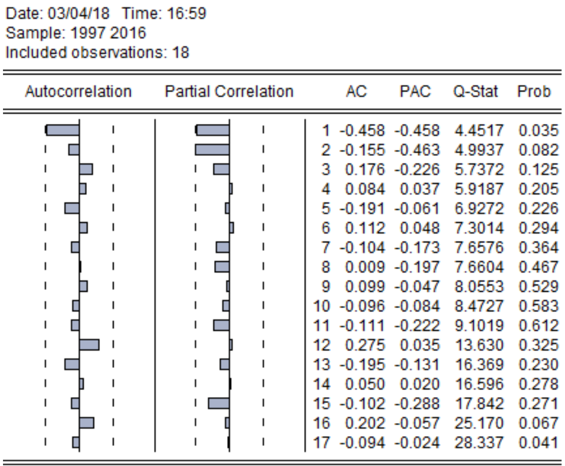
(b)

Figure 4.14: ADF test for African region: (a) 1st difference (b) 2nd difference

The ADF test for 1st difference (Figure 4.14(a)) and 2nd difference (Figure 4.14(b)) of log transformation of original series has shown. According to the output, ADF test for 2nd difference of log transformed series confirms that the series is stationary at 5% significance level (p=0.0006).

4.5.2 Model Identification and Parameters Estimation

By observing the ACF plots and PACF plots of the stationary series can be used to tentatively recognize the order of autoregressive or moving average terms (Robert 2005). As per the ACF and PACF plot in Figure 4.16, in ACF the first spike and in PACF first and second lag has cut off the boundaries.



Date: 03/04/18 Time: 16:59
Sample: 1997 2016
Included observations: 18

	AC	PAC	Q-Stat	Prob
1	-0.458	-0.458	4.4517	0.035
2	-0.155	-0.463	4.9937	0.082
3	0.176	-0.226	5.7372	0.125
4	0.084	0.037	5.9187	0.205
5	-0.191	-0.061	6.9272	0.226
6	0.112	0.048	7.3014	0.294
7	-0.104	-0.173	7.6576	0.364
8	0.009	-0.197	7.6604	0.467
9	0.099	-0.047	8.0553	0.529
10	-0.096	-0.084	8.4727	0.583
11	-0.111	-0.222	9.1019	0.612
12	0.275	0.035	13.630	0.325
13	-0.195	-0.131	16.369	0.230
14	0.050	0.020	16.596	0.278
15	-0.102	-0.288	17.842	0.271
16	0.202	-0.057	25.170	0.067
17	-0.094	-0.024	28.337	0.041

Figure 4.15: ACF/PACF Log converted 2nd Difference (African imports)

Observing Figure 4.15 of ACF and PACF of differenced model, following models were tested.

Table 4.7: Comparison of Univariate models for African region

Model	Model coefficients	AIC	SC
ARIMA(0,2,1)	Not significant	1.329	0.4406
ARIMA(1,2,1)	Not significant	1.1002	0.6703
ARIMA(2,2,1)	Not significant	0.9926	0.4653
ARIMA(1,2,0)	Significant	0.089	0.2378
ARIMA(2,2,0)	Not significant	0.9043	0.2434

As per the comparison of univariate models which are shown in Table 4.7 indicates that ARIMA (1,2,0) model is better among all tested models.

Table 4.8: Model Significance- Univariate Africa

<table>
<tr><th>Model</th><th>Model coeficients & adequateness</th></tr>
<tr><td>Model 1 :
ARIMA (1,2,0)

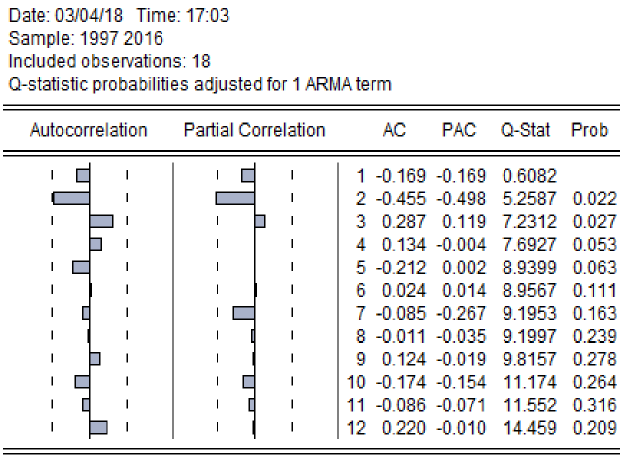
EViews Equation

d(LN_AFRICA,2) c ar(1)</td><td>
<table>
<tr><th>Variable</th><th>Coefficient</th><th>Std. Error</th><th>t-Statistic</th><th>Prob.</th></tr>
<tr><td>C</td><td>-0.013942</td><td>0.044002</td><td>-0.316861</td><td>0.7557</td></tr>
<tr><td>AR(1)</td><td>-0.586112</td><td>0.248255</td><td>-2.360921</td><td>0.0322</td></tr>
<tr><td>SIGMASQ</td><td>0.044817</td><td>0.021202</td><td>2.113820</td><td>0.0517</td></tr>
</table>
<table>
<tr><td>R-squared</td><td>0.289365</td><td>Mean dependent var</td><td>-0.020603</td></tr>
<tr><td>Adjusted R-squared</td><td>0.194614</td><td>S.D. dependent var</td><td>0.258409</td></tr>
<tr><td>S.E. of regression</td><td>0.231905</td><td>Akaike info criterion</td><td>0.089414</td></tr>
<tr><td>Sum squared resid</td><td>0.806698</td><td>Schwarz criterion</td><td>0.237810</td></tr>
<tr><td>Log likelihood</td><td>2.195271</td><td>Hannan-Quinn criter.</td><td>0.109876</td></tr>
<tr><td>F-statistic</td><td>3.053946</td><td>Durbin-Watson stat</td><td>2.119918</td></tr>
<tr><td>Prob(F-statistic)</td><td>0.077152</td><td></td><td></td></tr>
</table>
</td></tr>
</table>

Table 4.8 shows that model coefficient is significance in ARIMA(1,2,0). ARIMA(1,2,0) having lower AIC value(0.0894) and SC (0.2378) indicates that model fits appropriately.

4.5.3 Residual Diagnostics

Residual diagnostic is the other important test to validating the model.



Date: 03/04/18 Time: 17:03
Sample: 1997 2016
Included observations: 18
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.169	-0.169	0.6082	
		2	-0.455	-0.498	5.2587	0.022
		3	0.287	0.119	7.2312	0.027
		4	0.134	-0.004	7.6927	0.053
		5	-0.212	0.002	8.9399	0.063
		6	0.024	0.014	8.9567	0.111
		7	-0.085	-0.267	9.1953	0.163
		8	-0.011	-0.035	9.1997	0.239
		9	0.124	-0.019	9.8157	0.278
		10	-0.174	-0.154	11.174	0.264
		11	-0.086	-0.071	11.552	0.316
		12	0.220	-0.010	14.459	0.209

Figure 4.16: Correlogram of residuals model ARIMA (1,2,0),African region

As shown in Figure 4.16 correlogram of the residuals confirm the white noise of residuals.

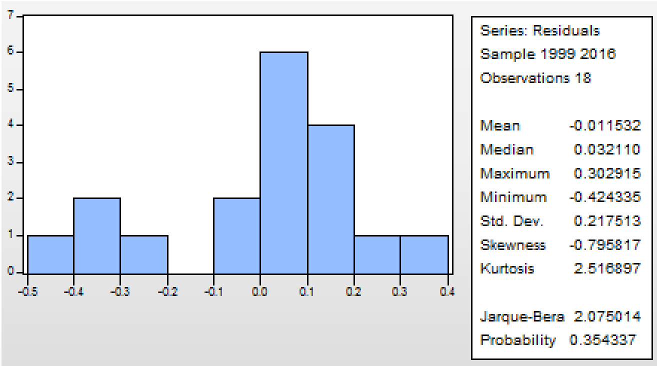


Figure 4.17: JB test for residuals model ARIMA 1,2,0 African region

According to the Figure 4.17 JB test is not significant (p=0.35) and it confirms that the residuals are normally distributed

Heteroskedasticity Test: ARCH

F-statistic	1.659342	Prob. F(1,15)	0.2172
Obs*R-squared	1.693273	Prob. Chi-Square(1)	0.1932

Figure 4.18: ARCH test for residuals in model ARIMA 1,2,0 African region

Figure 4.18 illustrates that the results of testing heteroscedasticity for residuals. Probability of chi square is not significant (observed R-squared 1.693, p 0.1932) and it indicates that there is no ARCH effect.

4.5.4 Fitted Model for African Region Glazed Tiles Imports

Based on above outcome ARIMA(1,2,0) model can be recommend to forecast the export potential of ceramic glazed tiles in African region. Derived model can represent as below.

ARIMA (1, 2, 0)

Y”= μ + ϕ1 Y”$_{t-1}$ + e_t ; Where Y”= [Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)]

Y”= -0.014 - 0.59 Y”$_{t-1}$ + 0.045 ; Where Y”= [Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)]

[Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)] = -0.014 - 0.59 [Y (t-1) –Y (t-2)] -[Y (t-2) – Y (t-3)] + 0.045

Y(t) = 1.41Y(t-1) +1.118Y(t-2) -0.59Y(t-3) + 0.031

Here Y(t) is log converted series (Y(t) =lnX(t))

lnX(t) = 1.41ln[X(t-1)] +0.18ln[X(t-2)] -0.59ln[X(t-3)] + 0.031

4.6 Forecasting Imports of Ceramic Glazed Tiles by Asian Region

Imports of ceramic glazed tiles in Asian region varies between $2.02*10^9$ (max) and $3.79*10^8$(min) with the mean of $1.07*10^9$as per the Table 4.9. The data seems positively skewed (skewness 0.39). Also JB=1.92 test and p value is not significant (p = 0.38) .Thus it confirms that data are normally distributed. The original series variation is quite larger. Thus original series has converted to logarithmic series.

Table 4.9: Descriptive Statistics of Asian region original and log converted series

	Mean	Max	Min	Std. Dev.	Skewness	Jarque-Bera	Prob.
ASIA	1.07E+09	2.02E+09	3.79E+08	5.80E+08	0.392519	1.90702	0.385385
LN_ASIA	20.64149	21.42629	19.75413	0.580311	-0.09052	1.64620	0.439068

Log converted series varies between 19.75 (min) and 21.42(max) with the mean of 21.42. According to the Table 4.9 and data seems negatively skewed (Skewness 0.090). Also JB=1.64 and *p* value is not significant (p = 0.439).

4.6.1 Stationarity of Asia Log Converted Series

Stationarity of series is very desirable factor and this can be recognized through the correlagram of the series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.894	0.894	18.513	0.000
		2	0.765	-0.171	32.822	0.000
		3	0.580	-0.349	41.534	0.000
		4	0.409	-0.005	46.126	0.000
		5	0.239	-0.056	47.799	0.000
		6	0.093	-0.053	48.073	0.000
		7	-0.031	-0.035	48.105	0.000
		8	-0.113	0.051	48.571	0.000
		9	-0.216	-0.298	50.432	0.000
		10	-0.276	0.052	53.794	0.000
		11	-0.378	-0.297	60.766	0.000
		12	-0.432	0.054	71.032	0.000

Figure 4.19: Correlogram of level (Log converted Asian imports)

Null Hypothesis: LN_ASIA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	0.082391	0.9554

Figure 4.20: ADF test (Log converted Asian imports)

Correlagram (Figure 4.19) and ADF test (Figure 4.20) of the log converted series of Asian region emphasize that the series is not stationary at the level.

Null Hypothesis: D(LN_ASIA) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.414413	0.0808

(a)

Null Hypothesis: D(LN_ASIA,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.605912	0.0024

(b)

Figure 4.21: ADF Test Asian region (a) 1st difference (b) 2nd difference

According to the Figure 4.21, ADF test for 1st difference (Figure 4.21(a)) and 2nd difference (Figure 4.21(b)) of logarithmic transformation of original series has shown. The output, ADF test for 2nd difference of log series confirms that the series is stationary at 5% significance level (p=0.0024).

4.6.2 Model Identification and Parameters Estimation

Similar to earlier cases tried several models as ARIMA(0,2,1), ARIMA(1,2,1), ARIMA(2,2,1), ARIMA(1,2,0) & ARIMA(2,2,0).

Table 4.10: Comparison of Univariate models for Asia region

Model	**Model coefficients**	**AIC**	**SC**
ARIMA(0,2,1)	Not significant	0.859	0.710
ARIMA(1,2,1)	Not significant	0.789	0.592
ARIMA(2,2,1)	Not significant	0.678	0.431
ARIMA(1,2,0)	Significant	0.258	0.110
ARIMA(2,2,0)	Not significant	0.757	0.559

As per the comparison of univariate models which are shown in Table 4.10 indicates that ARIMA (1,2,0) model is better among all tested models.

Table 4.11: Model Significance- Univariate Asia

Model	Model coeficients & adequateness
Model 1 : ARIMA (1,2,0) **EViews Equation** d(LN_ASIA,2) c ar(1)	(see output below)

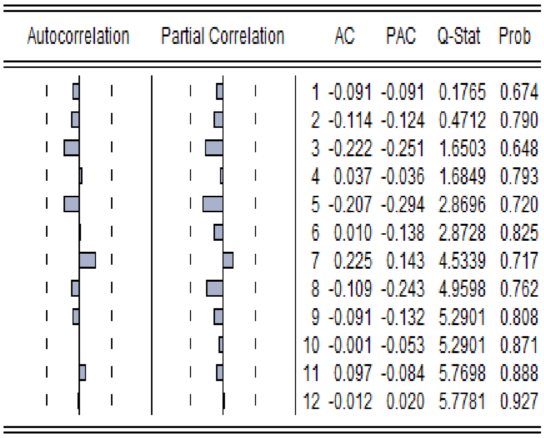
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.015387	0.033859	0.454436	0.6560
AR(1)	-0.684567	0.243938	-2.806315	0.0133
SIGMASQ	0.031270	0.008597	3.637158	0.0024

R-squared	0.506770	Mean dependent var	0.019778
Adjusted R-squared	0.441006	S.D. dependent var	0.259092
S.E. of regression	0.193712	Akaike info criterion	-0.258747
Sum squared resid	0.562866	Schwarz criterion	-0.110352
Log likelihood	5.328723	Hannan-Quinn criter.	-0.238285
F-statistic	7.705895	Durbin-Watson stat	2.090569
Prob(F-statistic)	0.004987		

As per Table 4.11, the model coefficient is significant in ARIMA(1,2,0). Lower AIC value (0.258) and SC (0.110) values indicate that the model fits appropriately.

4.6.3 Residual Diagnostics

Similar to earlier cases, residual diagnostic has been carried out to validate the model.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.091	-0.091	0.1765	0.674
		2	-0.114	-0.124	0.4712	0.790
		3	-0.222	-0.251	1.6503	0.648
		4	0.037	-0.036	1.6849	0.793
		5	-0.207	-0.294	2.8696	0.720
		6	0.010	-0.138	2.8728	0.825
		7	0.225	0.143	4.5339	0.717
		8	-0.109	-0.243	4.9598	0.762
		9	-0.091	-0.132	5.2901	0.808
		10	-0.001	-0.053	5.2901	0.871
		11	0.097	-0.084	5.7698	0.888
		12	-0.012	0.020	5.7781	0.927

Figure 4.22: Correlogram of residuals model ARIMA 1,2,0 Asia region

As shown in Figure 4.22 the correlogram of the residuals confirm the white noise of residuals.

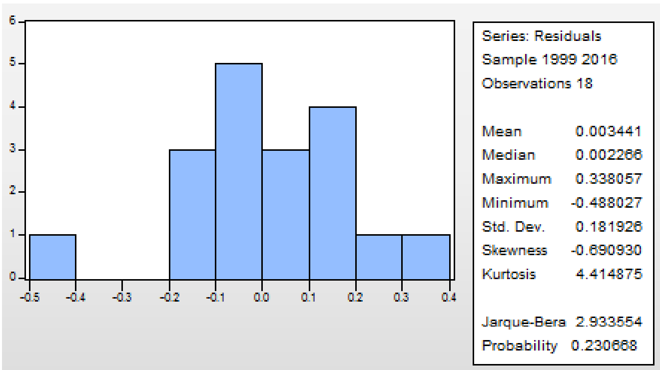


Figure 4.23: JB Test for residuals model ARIMA 1,2,0 Asia region

According to the Figure 4.23 the JB test is not significant (p=0.23) and it confirms that the residuals are normally distributed.

Heteroskedasticity Test: ARCH			
F-statistic	0.130136	Prob. F(1,15)	0.7233
Obs*R-squared	0.146219	Prob. Chi-Square(1)	0.7022

Figure 4.24: ARCH test for ARIMA 1,2,0 Asia region

Heteroskedasticity test shown in Figure 4.24 illustrates that probability of chi square is not significant (observed R-squared 0.146, p 0.702) and it reveals that there is no ARCH effect present.

4.6.4 Fitted Model for Asian Region Glazed Tiles Imports

Thus, based on above outcome, can be recommend that ARIMA(1,2,0) model to forecast the export potential of ceramic glazed tiles to Asian region. The derived model can be represented as below:

ARIMA (1, 2, 0)

Y”= μ + ϕ1 Y”$_{t-1}$ + e_t ; Where Y”= [Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)]

Y”= 0.015358 - 0.684567 Y”$_{t-1}$ + 0.031270 ; Where Y”= [Y (t) –Y (t-1)] -[Y (t-1) – Y (t-2)]

[Y (t) –Y (t-1)] -[Y (t-1) –Y (t-2)] = 0.015358 -0.684567 [Y (t-1) –Y (t-2)] -[Y (t-2) – Y (t-3)] + 0.031270

Y(t) = 1.3154Y(t-1) +0.3692Y(t-2) -0.6846Y(t-3) + 0.0466

Here Y(t) is log converted series (Y(t) =lnX(t))

lnX(t) = 1.3154ln[X(t-1)] +0.3692ln[X(t-2)] -0.6846ln[X(t-3)] + 0.0466

4.7 Summary of Chapter 4

Annual ceramic glazed tiles exports from Sri Lanka to other countries has been reviewed and determined that there is no significant improvement in the business according to the 1997 to 2016 figures. Also found that the export market is highly reliant on Oceania and NA regional markets. With respect to construction growth rates and market accessibility it is found that there may be more opportunity in ME, Africa, and Asian regions. Therefore, in these three regions the annual ceramic imports have been analysed using univariate forecasting techniques. Irrespective of the region these three markets can be forecasted using ARIMA(1,2,0) model.

CHAPTER 5

FORECASTING OF REGIONAL CERAMIC GLAZED TILES IMPORTS – MULTIVARIATE APPROACH

This chapter has been devoted to multivariate forecasting of regional ceramic glazed tiles imports that are expecting to have high, moderate and low opportunity markets.

5.1 Multivariate Forecasting for Regions Where Opportunity High

5.1.1 Optimal Lag Length

VAR models can be developed for stationary series at level or series which can be transforming to stationary in same lag. From the above analysis we came across that our series can be convert to stationary at the same level of difference and prior to estimating a VAR model the appropriate number of lags has to be specified. Further to the analysis of the previous chapter, three variables of log converted series ME, Africa and Asian imports of ceramic glazed tiles has been reviewed under a multivariate approach.

Table 5.1: Lag order selection

VAR Lag Order Selection Criteria
Endogenous variables: LN_AFRICA LN_ASIA LN_ME
Exogenous variables: C
Date: 08/15/18 Time: 22:30
Sample: 1997 2016
Included observations: 18

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-0.650769	NA	0.000301	0.405641	0.554036	0.426103
1	44.92930	70.90232*	5.29e-06*	-3.658811*	-3.065229*	-3.576964*
2	51.15485	7.609014	8.01e-06	-3.350539	-2.311769	-3.103307

Using popular likelihood ratios such as Akaike and Schwarz- information criteria the optimal lag length can be determined (Keating, 1995). Table 5.1.shows the number of lags recommended by the selected criteria. According to the information criterions which are AIC,SC and HQ indicates the optimal lag length is 1.All the variables are non stationary and they can be made stationary at the same level of difference. Thus, cointegration tests can be appliedover three series over lag length 1.

5.1.2 Cointegration Test

Using the identified optimal lag length we can decide which type of model would suit using cointegration test. If we found significant cointegration or long run association, we can determine VEC type or cointegrated VAR model. If not, we can determine VAR type model.

Table 5.2: Cointegration test (Trace)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.638050	33.84834	29.79707	0.0162
At most 1 *	0.521803	15.55587	15.49471	0.0490
At most 2	0.118811	2.276700	3.841466	0.1313

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

According to the Table 5.2 of cointegration rank test of trace reject the null hypothesis up to at most 1. This reflects the need of two cointegration equations and VEC type of approach can be used.

Table 5.3: Cointegration test (Maximum eigenvalue)

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.638050	18.29247	21.13162	0.1193
At most 1	0.521803	13.27917	14.26460	0.0711
At most 2	0.118811	2.276700	3.841466	0.1313

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

But according to the Table 5.3 of cointegration rank test of maximum eigen value accept the null hypothesis up to at most 2. Max eigen statistics (2.27) < Critical value(3.84) and not significant(p=0.1313). This reflects the VAR type approach is suitable. The trace test indicates that in the long run these variables move together. In other words, we can say that there is a significant long term association and requirement of the error correction model (VEC). On the other hand, the Max eigen value test indicates that there is no significant long term association and that the VAR type of model can be used in forecasting

5.1.3 VEC Model

Based on trace test tried VEC model by having two cointegrated equations

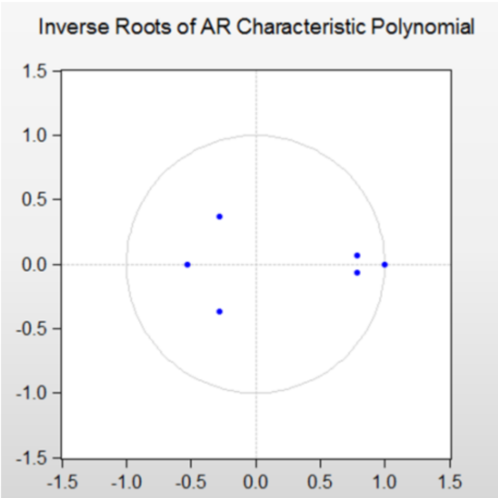
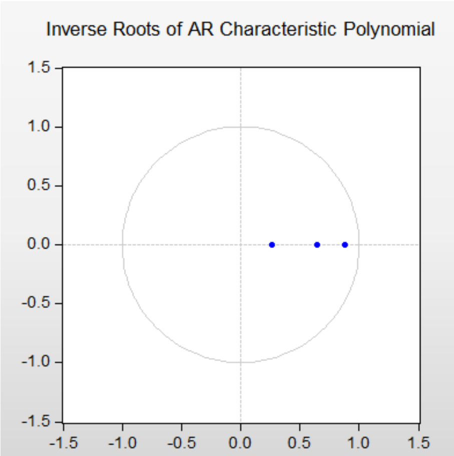


Figure 5.1: Model stability (VEC model for ME,Africa& Asia)

According to the Figure 5.1, stability failed in the VEC model by observing inverse roots of characteristics polynomial. One root that has lye over the unit root circle confirms the poor stability of VEC model.

5.1.4 VAR model

If modulus values are less than 1, it is said to be a stable process (Lutkepohl, 2007). A stable process is one that will not deviate to infinity. A vital fact is that stability indicates stationarity and it is adequate to test for stability to ensure that a VAR process is suitable and stationary. According to the Figure 5.2 of inverse roots of characteristics polynomials we found that all the roots are lye within a unit root circle and all the modulus values are less than one. Thus derived VAR(1) model satisfies the stability condition.



Roots of Characteristic Polynomial
Endogenous variables: LN_AFRICA LN_ASIA LN_ME
Exogenous variables: C
Lag specification: 1 1
Date: 07/04/18 Time: 23:44

Root	Modulus
0.881737	0.881737
0.649246	0.649246
0.267343	0.267343

No root lies outside the unit circle.
VAR satisfies the stability condition.

Figure 5.2: Model stability (VAR model ME, Africa, Asia)

5.1.5 Causality Test

The Granger-causality test is conducted over the VAR(1) model which has been developed. The output is interpreted in Table 5.4.

Table 5.4: Granger causality

Null Hypothesis:	Obs	F-Statistic	Prob.
LN_ASIA does not Granger Cause LN_AFRICA	18	1.25731	0.3168
LN_AFRICA does not Granger Cause LN_ASIA		2.95564	0.0875
LN_ME does not Granger Cause LN_AFRICA	18	5.18805	0.0221
LN_AFRICA does not Granger Cause LN_ME		0.32126	0.7308
LN_ME does not Granger Cause LN_ASIA	18	3.87745	0.0478
LN_ASIA does not Granger Cause LN_ME		0.61471	0.5558

The results for the VAR(1) model which represents on Table 5.4 suggests that some variables are caused on each other. The results reveal that Africa does unidirectional Granger caused by the Asian region at 10% of significant level and ME region unidirectional Granger-caused by both African and Asian imports at 5% significance level.

Table 5.5: Wald Test

VAR Lag Exclusion Wald Tests
Date: 04/23/19 Time: 22:32
Sample: 1997 2016
Included observations: 19

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	LN_AFRICA	LN_ASIA	LN_ME	Joint
Lag 1	404.6144 [0.0000]	786.1312 [0.0000]	617.5497 [0.0000]	1106.356 [0.0000]
df	3	3	3	9

Moreover, using lag exclusion Wald test as per Table 5.5,it was found that all the variables at 1st lag are jointly significant and should be, therefore, included in the model.

5.1.6 VAR Model Estimation –ME Region Ceramic Glazed Tiles Imports

VAR(1) model has run for three variables that were analyzed so far. The output has given three consecutive equations of tri-variate models. Initially, model coefficients and adequateness should be checked with respect to finding out the coefficient significance by using the Procs and OLS estimations in E views separately run the model which identified for ME market.

Dependent Variable: LNME
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 08/15/18 Time: 22:50
Sample (adjusted): 1998 2016
Included observations: 19 after adjustments
LN_ME = C(9)*LN_AFRICA(-1) + C(10)*LN_ASIA(-1) + C(11)*LN_ME(-1) + C(12)

	Coefficient	Std. Error	t-Statistic	Prob.
C(9)	0.096964	0.144960	0.668905	0.5137
C(10)	-0.079498	0.148083	-0.536846	0.5992
C(11)	0.828201	0.097804	8.468004	0.0000
C(12)	3.359844	1.305941	2.572737	0.0212

R-squared	0.976539	Mean dependent var	20.60722
Adjusted R-squared	0.971847	S.D. dependent var	0.674906
S.E. of regression	0.113242	Akaike info criterion	-1.333916
Sum squared resid	0.192356	Schwarz criterion	-1.135087
Log likelihood	16.67221	Hannan-Quinn criter.	-1.300267
F-statistic	208.1195	Durbin-Watson stat	2.786427
Prob(F-statistic)	0.000000		

Figure 5.3: Modeladequateness of VAR model for ME region

According to the output of Figure 5.3, it was noted that only the C(11) coefficient is individually significant and represents the 1st lag of log converted ME series. Though other individual coefficients seem to be insignificant, we can observe that this model seems significant due to F=208.11(p=0.000). This reflects those coefficients are cause jointly significant. Further R squared value represent that model capable to explain 97% of the variability and model seems adequate.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.089	-0.089	0.1756	0.675
		2	-0.032	-0.040	0.1991	0.905
		3	-0.244	-0.253	1.6810	0.641
		4	-0.062	-0.120	1.7836	0.775
		5	-0.134	-0.195	2.2939	0.807
		6	0.464	0.393	8.9025	0.179
		7	-0.047	-0.030	8.9757	0.254
		8	-0.071	-0.127	9.1571	0.329
		9	-0.117	0.028	9.7027	0.375
		10	0.080	0.145	9.9850	0.442
		11	-0.172	-0.124	11.455	0.406
		12	0.049	-0.272	11.591	0.479

Figure 5.4: Correlagram of squared residuals (VAR model for ME)

According to the Figure 5.4, the correlogram of squared residuals confirm the white noise of residuals.

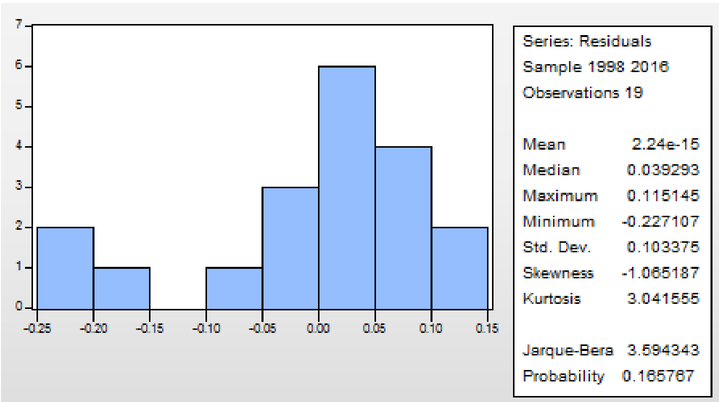


Figure 5.5: JB test for residuals (VAR model for ME)

As shown in Figure5.5,JB test is not significant (p=0.16) and it confirms that the residuals are normally distributed.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.459090	Prob. F(2,13)	0.1242
Obs*R-squared	5.215117	Prob. Chi-Square(2)	0.0737

Figure 5.6: Breush Godfrey test for residuals (VAR-ME)

According to the Breush Godfrey test shown in Figure 5.6, there is no serial correlation present (Obs R sq=5.21, p=0.0737).

Heteroskedasticity Test: ARCH

F-statistic	0.130397	Prob. F(1,16)	0.7227
Obs*R-squared	0.145511	Prob. Chi-Square(1)	0.7029

Figure 5.7: Arch test for residuals (VAR-ME)

Figure 5.7 Illustrates that the results for testing heteroscedasticity of the residuals.Probabilityof Chi squared not significant (p=0.70) and it concludes that there is no ARCH effects in the model.

5.1.7 Fitted VAR Model for ME RegionGlazed Tiles Imports

Thus based on above outcome, it can be recommended that the VAR(1) model could be used to forecast the export potential of ceramic glazed tiles to the Middle East region. The derived model of VAR (1) process for the Middle East market can be represent as below:

LN_ME (t) = C(9)*LN_AFRICA(t-1) + C(10)*LN_ASIA(t-1) + C(11)*LN_ME(t-1) + C(12)

$$X_t = C(9)Z_{t-1} + C(10)Y_{t-1} + C(11)X_{t-1} + C(12)$$

$$X_t = 0.096964Z_{t-1} - 0.079498Y_{t-1} + 0.828201X_{t-1} + 3.359844$$

Where: $ME_t = \exp(X_t)$

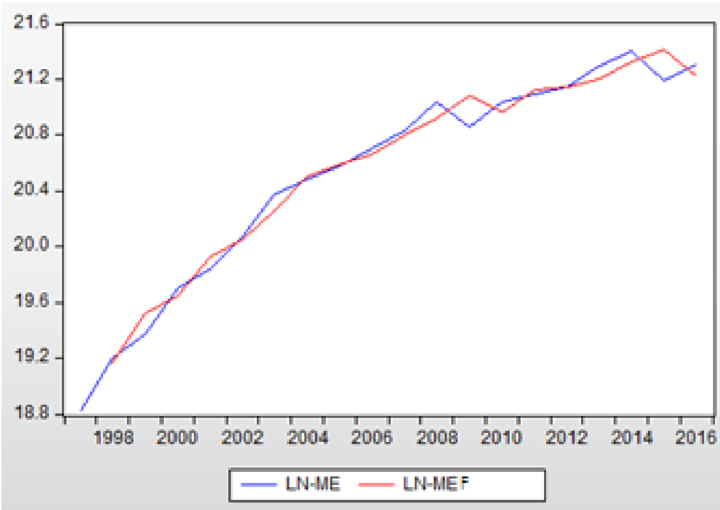


Figure 5.8: Actual vs Forecasted (VAR model ME region)

Based on model outcome represent above, the actual vs. forecasted plots showed in Figure 5.8.

5.1.8 VAR Model Estimation –Asia Region Ceramic Glazed Tiles Imports

VAR(1) model has run for three variables that we analysed so far. The output has given three consecutive equations of tri-variate models. To find out the significance of coefficients separately run the model which identified for Asian market in OLS estimations in E views.

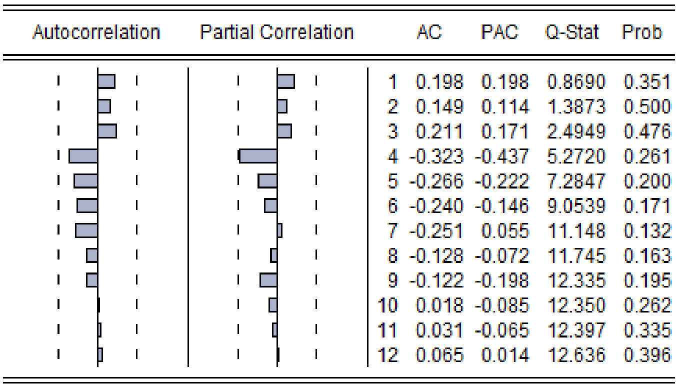
Dependent Variable: LN_ASIA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 08/15/18 Time: 22:48
Sample (adjusted): 1998 2016
Included observations: 19 after adjustments
LN_ASIA = C(5)*LN_AFRICA(-1) + C(6)*LN_ASIA(-1) + C(7)*LN_ME(-1) + C(8)

	Coefficient	Std. Error	t-Statistic	Prob.
C(5)	0.170809	0.163540	1.044450	0.3128
C(6)	0.429003	0.167063	2.567920	0.0214
C(7)	0.283066	0.110339	2.565416	0.0215
C(8)	2.632335	1.473326	1.786662	0.0942

R-squared	0.960982	Mean dependent var	20.65963
Adjusted R-squared	0.953179	S.D. dependent var	0.590419
S.E. of regression	0.127756	Akaike info criterion	-1.092720
Sum squared resid	0.244825	Schwarz criterion	-0.893891
Log likelihood	14.38084	Hannan-Quinn criter.	-1.059071
F-statistic	123.1467	Durbin-Watson stat	2.839336
Prob(F-statistic)	0.000000		

Figure 5.9: Model adequateness (VAR model Asia region)

According to the output of Figure 5.9, it was noted that both C(6) and C(7) coefficients are individually significant. Though other individual coefficients does not seem to be significant, we can observe that a model seems to be significant due to F=123.14(p=0.000). This reflects that those coefficients are cause jointly significant. Furthermore, the R squared value represents that the model is capable of explaining 96% of the variability and the model seems to be adequate.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.198	0.198	0.8690	0.351
		2	0.149	0.114	1.3873	0.500
		3	0.211	0.171	2.4949	0.476
		4	-0.323	-0.437	5.2720	0.261
		5	-0.266	-0.222	7.2847	0.200
		6	-0.240	-0.146	9.0539	0.171
		7	-0.251	0.055	11.148	0.132
		8	-0.128	-0.072	11.745	0.163
		9	-0.122	-0.198	12.335	0.195
		10	0.018	-0.085	12.350	0.262
		11	0.031	-0.065	12.397	0.335
		12	0.065	0.014	12.636	0.396

Figure 5.10: Correlagram of squared residuals (VAR model for Asia)

According to the Figure 5.10, the correlogram of squared residuals confirm the white noise of residuals.

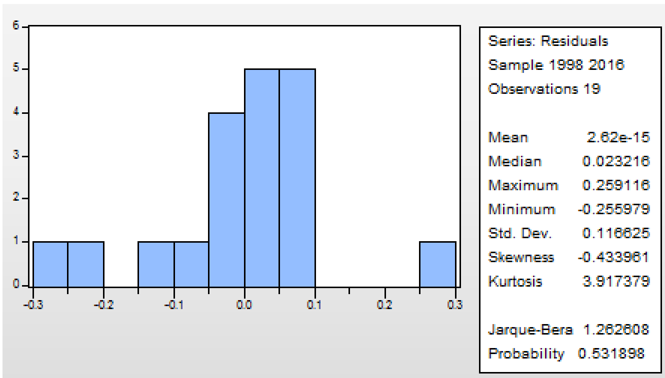


Figure 5.11: JB test for residuals (VAR model for Asia)

As shown in Figure 5.11, the JB test is not significant (p=0.53) and it confirms that the residuals are normally distributed.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.581612	Prob. F(2,13)	0.1137
Obs*R-squared	5.401093	Prob. Chi-Square(2)	0.0672

Figure 5.12: Breusch- Godfrey test for residuals (VAR model for Asia)

According to the Figure 5.12theBreush Godfrey testis not significant (Obs R sq=5.4, p=0.067) and it could be concluded that there is no serial correlation present.

Heteroskedasticity Test: ARCH

F-statistic	0.661975	Prob. F(1,16)	0.4278
Obs*R-squared	0.715134	Prob. Chi-Square(1)	0.3977

Figure 5.13: Heteroskedasticity test for residuals(VAR model for Asia)

Figure 5.13 Illustrates that the results for testing heteroscedasticity of the residuals.Probabilityof Chi squared is not significant (p=0.39) and it concludes that there is no ARCH effects in the model.

5.1.9 Fitted VAR Model for Asia Region Glazed Tiles Imports

Based on the above outcome, it can be recommend that the VAR(1) model is suitable to forecast the export potential of ceramic glazed tiles to the Asian region. The derived model can be represented as shown below:

LN-ASIA(t) = C(5)*LN-AFRICA(t-1) + C(6)*LN-ASIA(t-1) + C(7)*LN-ME(t-1) + C(8)

$$Y_t = C(5)Z_{t-1} + C(6)Y_{t-1} + C(7)X_{t-1} + C(8)$$

$$Y_t = 0.170809Z_{t-1} + 0.429003Y_{t-1} + 0.283066X_{t-1} + 2.632335$$

Where: $Asia_t = \exp(Y_t)$

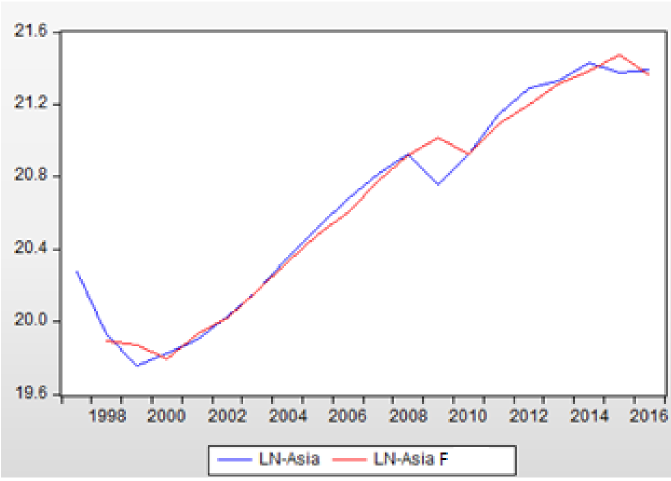


Figure 5.14: Actual vs Forecasted (VAR Model for Asian region)

Based on the above outcome, we can represent the actual and forecasted plot of the Asian region according to Figure 5.14.

5.1.10 VAR Model Estimation –Africa Region Ceramic Glazed Tiles Imports

The African market also tried over VAR model with respect to finding out the significance of coefficients by using the Procs and OLS estimations in E views for African market.

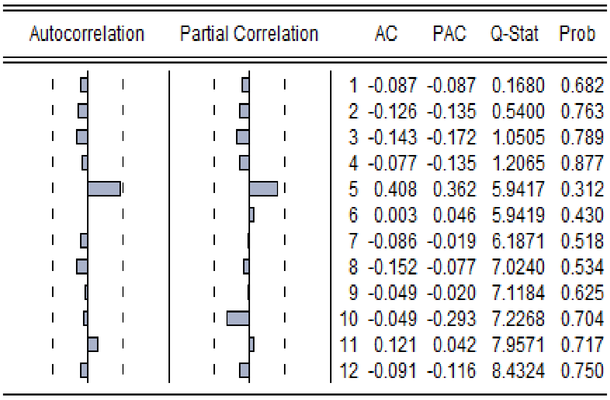
Dependent Variable: LN_AFRICA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 08/15/18 Time: 22:45
Sample (adjusted): 1998 2016
Included observations: 19 after adjustments
LN_AFRICA = C(1)*LN_AFRICA(-1) + C(2)*LN_ASIA(-1) + C(3)*LN_ME(-1) + C(4)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.433068	0.195364	2.216723	0.0425
C(2)	0.403007	0.199573	2.019351	0.0617
C(3)	0.256466	0.131811	1.945715	0.0707
C(4)	-2.188619	1.760032	-1.243511	0.2328

R-squared	0.966776	Mean dependent var	19.96815
Adjusted R-squared	0.960131	S.D. dependent var	0.764338
S.E. of regression	0.152617	Akaike info criterion	-0.737101
Sum squared resid	0.349381	Schwarz criterion	-0.538272
Log likelihood	11.00246	Hannan-Quinn criter.	-0.703451
F-statistic	145.4920	Durbin-Watson stat	1.758280
Prob(F-statistic)	0.000000		

Figure 5.15: Model adequateness (VAR Model for African region)

According to the output of Figure 5.15, it was noted that coefficients C(1) are individually significant. Though other individual coefficients do not seem to be significant, we can observe that the model seems significant due to F=145.49(p=0.000). This reflects those coefficients are cause jointly significant. Furthermore, the R squared value indicates that the model is capable of explaining 96% of the variability and that the model seems adequate.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.087	-0.087	0.1680	0.682
		2	-0.126	-0.135	0.5400	0.763
		3	-0.143	-0.172	1.0505	0.789
		4	-0.077	-0.135	1.2065	0.877
		5	0.408	0.362	5.9417	0.312
		6	0.003	0.046	5.9419	0.430
		7	-0.086	-0.019	6.1871	0.518
		8	-0.152	-0.077	7.0240	0.534
		9	-0.049	-0.020	7.1184	0.625
		10	-0.049	-0.293	7.2268	0.704
		11	0.121	0.042	7.9571	0.717
		12	-0.091	-0.116	8.4324	0.750

Figure 5.16: Correlagram of residuals (VAR model Africa)

According to the Figure 5.16, the correlogram of squared residuals confirms the white noise of residuals

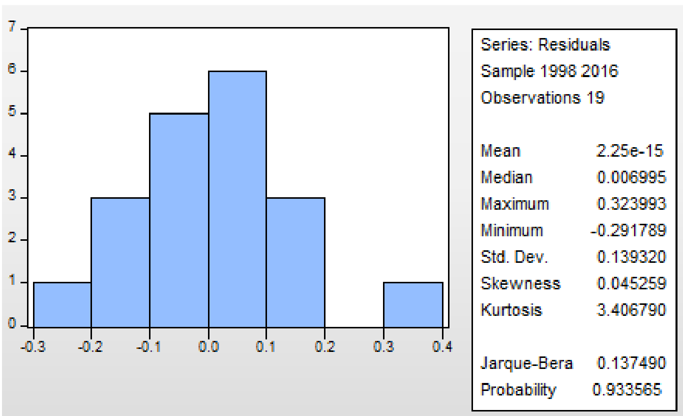


Figure 5.17: JB test for residuals (VAR model for Africa)

As shown in Figure 5.17, the JB test is not significant (p=0.93) and it confirms that the residuals are normally distributed.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.046310	Prob. F(2,13)	0.9549
Obs*R-squared	0.134409	Prob. Chi-Square(2)	0.9350

Figure 5.18: Breush Godfrey test for residuals (VAR model for Africa)

According to the Figure 5.18, the Breush Godfrey test is not significant (Obs R sq=0.134, p=0.93) and there is no serial correlation present.

Heteroskedasticity Test: ARCH

F-statistic	0.122550	Prob. F(1,16)	0.7309
Obs*R-squared	0.136821	Prob. Chi-Square(1)	0.7115

Figure 5.19: Heteroskedasticity test (VAR model for Africa)

Figure 5.19 illustrates the results for testing heteroscedasticity of the residuals.Probabilityof Chi squared is not significant (p=0.71) and it concludes that there is no ARCH effects in the model.

5.1.11 Fitted VAR Model for African Region Glazed Tiles Imports

Based on the above outcome, the VAR(1) model can be recommended to forecast the export potential of ceramic glazed tiles in the African region. The derived model can be represented as shown below:

LN_AFRICA(t) = C(1)*LN_AFRICA(t-1) + C(2)*LN_ASIA(t-1) + C(3)*LN_ME(t-1) + C(4)

$$Z_t = C(1)Z_{t-1} + C(2)Y_{t-1} + C(3)X_{t-1} + C(4)$$

$$Z_t = 0.433068Z_{t-1} + 0.403007Y_{t-1} + 0.256466X_{t-1} - 2.188619$$

Where$Africa_t = \exp(Z_t)$

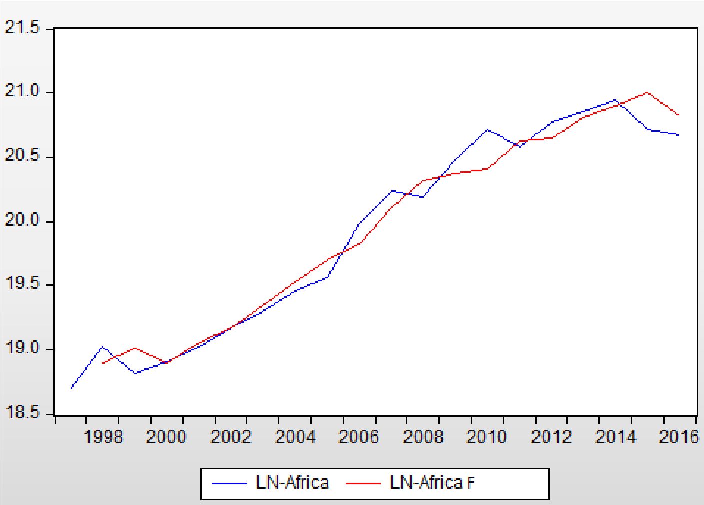


Figure 5.20: Actual vs Forecasted (VAR model African region)

Based on the above outcome, we can represent the actual and forecasted plot of the African region according to Figure 5.20.

5.2 Multivariate Forecasting for Regions Where Opportunity is Moderate

Similar to earlier approaches, multivariate forecasting methods have been applied over moderate potential markets in NA and Oceania. According to the current Sri Lanka export figures these markets have reached some extent. Through the analysis is expected to identify movement of these markets to figure out whether there is more opportunity.

5.2.1 Optimal Lag Length

In order to determine the appropriate number of lags checked the lag length selection criterion. Table 5.6 indicates the results of above mention likelihood ratio tests. The greatest statistic is the number of lags recommended by the selected criteria. Here we found that all information criterions which are AIC, SC and HQ indicate the optimal length is lag 2. All the variables are non stationary and they can be make stationary at the same level of difference.

Table 5.6: Lag order selection

VAR Lag Order Selection Criteria
Endogenous variables: NA OCEANIA
Exogenous variables: C
Date: 07/16/18 Time: 00:33
Sample: 1997 2016
Included observations: 18

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-717.4425	NA	1.79e+32	79.93805	80.03698	79.95169
1	-700.7790	27.77243*	4.40e+31	78.53100	78.82779*	78.57193
2	-695.3878	7.787245	3.86e+31*	78.37643*	78.87108	78.44463*

5.2.2 Cointegration Test

The cointegration test can be appliedoveroptimal lag length which was found above to decide whether VAR or VEC type approach need to followed. If we found a significant cointegration or long run association, we can determine the VEC type or cointegrated VAR model. If not, we can determine a VAR type model.

Table 5.7: Cointegration rank test VAR model NA & Oceania

Unrestricted Cointegration Rank Test (Trace)

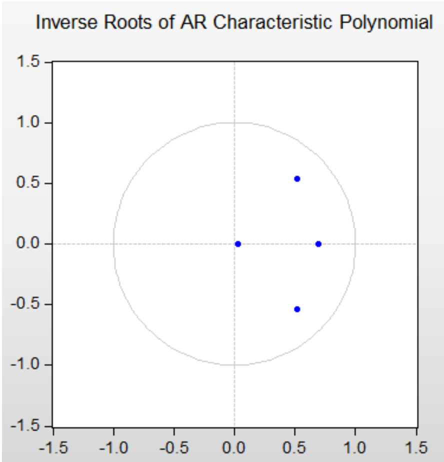
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.456681	11.39213	15.49471	0.1885
At most 1	0.058299	1.021143	3.841466	0.3122

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level

According to Table 5.7 of the Trace test of cointegration accepts the null hypothesis of no cointegration equation because Trace statistics are less than critical values and not significant (p=0.3122).Hence, we can say that there is no significant long run association between North American and Oceania regions. This indicates that a VAR type of model can be used in forecasting. Therefore, the VAR(2) model could run for optimal lag length and initially check the stability of model as shown below.

5.2.3 Stability of Model

If modulus values are less than 1, it is said to be a stable process (Lutkepohl, 2006). A stable process is one that will not deviate to infinity and a vital fact is that stability indicates stationarity and it is adequate to test for stability to ensure that a VAR process is both stable and stationary.



Roots of Characteristic Polynomial
Endogenous variables: NA OCEANIA
Exogenous variables: C
Lag specification: 1 2
Date: 07/16/18 Time: 00:35

Root	Modulus
0.519031 - 0.537675i	0.747320
0.519031 + 0.537675i	0.747320
0.691442	0.691442
0.029233	0.029233

No root lies outside the unit circle.
VAR satisfies the stability condition.

Figure 5.21: Stability of model(VAR model NA & Oceania)

According to the Figure 5.21 of inverse roots of characteristics polynomials we found that all the roots are lye within a unit root circle and all the modulus values are less than one. Thus derived VAR(2) model satisfies the stability condition for moderate potential markets.

Table 5.8: Wald test

VAR Lag Exclusion Wald Tests
Date: 07/16/18 Time: 00:35
Sample: 1997 2016
Included observations: 18

Chi-squared test statistics for lag exclusion:
Numbers in [ ] are p-values

	NA	OCEANIA	Joint
Lag 1	38.58819 [0.0000]	3.705953 [0.1568]	43.00253 [0.0000]
Lag 2	7.659079 [0.0217]	0.147643 [0.9288]	10.66097 [0.0307]
df	2	2	4

Moreover, to further investigate run the lag exclusion Wald test as per Table 5.8and found that all the variables at 1st and 2nd lag are jointly significant and should be, therefore, included in the model.

5.2.4 VAR Model Estimation –NA & Oceania Regional Ceramic Glazed Tiles Imports

Using the Procs and OLS estimations in E views separately run the model which identified for NA & Oceania market.

Dependent Variable: NA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 07/16/18 Time: 00:37
Sample (adjusted): 1999 2016
Included observations: 18 after adjustments
NA = C(1)*NA(-1) + C(2)*NA(-2) + C(3)*OCEANIA(-1) + C(4)*OCEANIA(-2) + C(5)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.399520	0.228591	6.122363	0.0000
C(2)	-0.716604	0.259742	-2.758912	0.0163
C(3)	-0.984804	1.714202	-0.574497	0.5754
C(4)	2.137048	1.627464	1.313115	0.2119
C(5)	3.47E+08	2.79E+08	1.244383	0.2353

R-squared	0.833917	Mean dependent var	1.98E+09
Adjusted R-squared	0.782814	S.D. dependent var	3.83E+08
S.E. of regression	1.79E+08	Akaike info criterion	41.06883
Sum squared resid	4.14E+17	Schwarz criterion	41.31615
Log likelihood	-364.6195	Hannan-Quinn criter.	41.10293
F-statistic	16.31851	Durbin-Watson stat	2.355030
Prob(F-statistic)	0.000055		

(a)

Dependent Variable: OCEANIA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 07/16/18 Time: 00:39
Sample (adjusted): 1999 2016
Included observations: 18 after adjustments
OCEANIA = C(6)*NA(-1) + C(7)*NA(-2) + C(8)*OCEANIA(-1) + C(9) *OCEANIA(-2) + C(10)

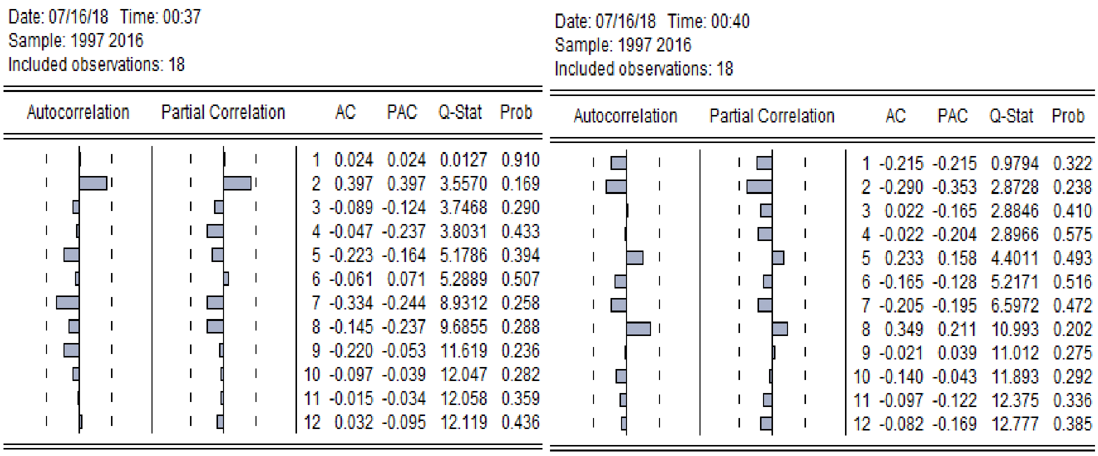
	Coefficient	Std. Error	t-Statistic	Prob.
C(6)	0.042375	0.038581	1.098357	0.2920
C(7)	0.016762	0.043838	0.382353	0.7084
C(8)	0.359217	0.289314	1.241613	0.2363
C(9)	-0.065739	0.274675	-0.239335	0.8146
C(10)	74382771	47006163	1.582405	0.1376

R-squared	0.667180	Mean dependent var	2.62E+08
Adjusted R-squared	0.564774	S.D. dependent var	45679698
S.E. of regression	30135667	Akaike info criterion	37.51045
Sum squared resid	1.18E+16	Schwarz criterion	37.75778
Log likelihood	-332.5941	Hannan-Quinn criter.	37.54455
F-statistic	6.515034	Durbin-Watson stat	1.926567
Prob(F-statistic)	0.004184		

(b)

Figure 5.22: model coefficients and adequateness, (a)-NA region (b)-Oceania region

According to the output of Figure 5.22(a), it was noted that only C(1) and C(2) coefficients are individually significant. Those coefficients represent the 1stand 2nd lag of NA region series. Though other individual coefficients do not seem to be significant, we can observe that the model seems significant due to F=16.31(p=0.000). This indicates that those coefficients are cause jointly significant. Further R squared value represent that the model is capable of explaining 83% of the variability and the model seems adequate. Similarly, the Oceania region (Figure 5.22b) also seems significant due to F=6.51(p=0.004). R squared value represents the model is capable of explaining 66.7% of the variability and the model seems adequate.



Date: 07/16/18 Time: 00:37
Sample: 1997 2016
Included observations: 18

	AC	PAC	Q-Stat	Prob
1	0.024	0.024	0.0127	0.910
2	0.397	0.397	3.5570	0.169
3	-0.089	-0.124	3.7468	0.290
4	-0.047	-0.237	3.8031	0.433
5	-0.223	-0.164	5.1786	0.394
6	-0.061	0.071	5.2889	0.507
7	-0.334	-0.244	8.9312	0.258
8	-0.145	-0.237	9.6855	0.288
9	-0.220	-0.053	11.619	0.236
10	-0.097	-0.039	12.047	0.282
11	-0.015	-0.034	12.058	0.359
12	0.032	-0.095	12.119	0.436

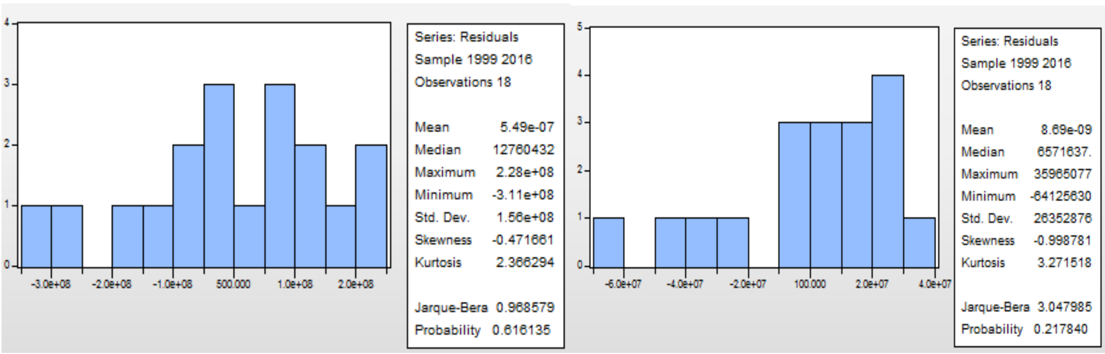
Date: 07/16/18 Time: 00:40
Sample: 1997 2016
Included observations: 18

	AC	PAC	Q-Stat	Prob
1	-0.215	-0.215	0.9794	0.322
2	-0.290	-0.353	2.8728	0.238
3	0.022	-0.165	2.8846	0.410
4	-0.022	-0.204	2.8966	0.575
5	0.233	0.158	4.4011	0.493
6	-0.165	-0.128	5.2171	0.516
7	-0.205	-0.195	6.5972	0.472
8	0.349	0.211	10.993	0.202
9	-0.021	0.039	11.012	0.275
10	-0.140	-0.043	11.893	0.292
11	-0.097	-0.122	12.375	0.336
12	-0.082	-0.169	12.777	0.385

(a) (b)

Figure 5.23: Correlagram of residuals, (a)-NA region (b)-Oceania region

The correlogram has run for the residuals for both NA (Figure 5.23a) and Oceania (Figure 5.23b) models. These correlogram of squared residuals confirm the white noise of residuals.



(a) (b)

Figure 5.24: Jarque Berra test for residuals, (a)-NA region (b)-Oceania region

The JB test which was carried out for NA (Figure 5.24a,p=0.61) and Oceania (Figure 5.24b, p=0.21) are not significant. It confirms that the residuals are normally distributed.

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.306757	Prob. F(2,11)	0.7419
Obs*R-squared	0.950898	Prob. Chi-Square(2)	0.6216

(a)

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.243684	Prob. F(2,11)	0.3259
Obs*R-squared	3.319597	Prob. Chi-Square(2)	0.1902

(b)

Figure 5.25: Breush Godfrey test, (a)-NA region (b)-Oceania region

Due to non-significance of Breusch Godfrey LM test and it's confirms that no serial correlation is present. NA region Obs R sq=3.31, p=0.19(Figure 5.25a) and Oceania Obs R sq=0.95, p=0.62(Figure 5.25b).

Heteroskedasticity Test: ARCH			
F-statistic	0.008420	Prob. F(1,15)	0.9281
Obs*R-squared	0.009538	Prob. Chi-Square(1)	0.9222

(a)

Heteroskedasticity Test: ARCH			
F-statistic	0.752263	Prob. F(1,15)	0.3994
Obs*R-squared	0.811850	Prob. Chi-Square(1)	0.3676

(b)

Figure 5.26: Hetroskedasticity test for Arch effect, (a)-NA region (b)-Oceania region

region Obs R sq=0.009, p=0.92 (Figure 5.27a) & Oceania Obs R sq=0.81, p=0.36(Figure 5.27b).

5.2.5 Fitted VAR Model for NA Region Glazed Tiles Imports

Thus based on the above outcome, it can be recommended that the VAR(2) model is suitable to forecast the export potential of ceramic glazed tiles to the NA region. The derived model can be presented as shown below:

NA(t) = C(1)*NA(t-1) + C(2)*NA(t-2) + C(3)*OCEANIA(-1) + C(4)*OCEANIA(-2) + C(5)

$$Z_t = C(1)Z_{t-1} + C(2)Z_{t-2} + C(3)X_{t-1} + C(4)X_{t-2} + C(5)$$

$$Z_t = 1.39952Z_{t-1} - 0.7166Z_{t-2} - 0.984804X_{t-1} + 2.137048X_{t-2} + 3.47E8$$

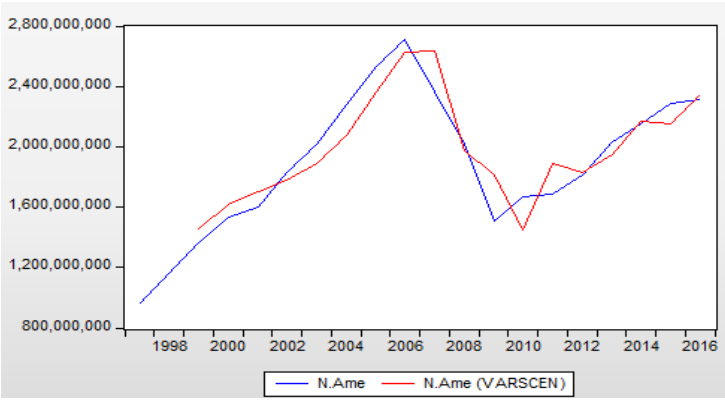


Figure 5.27: Actual vs Forecast (NA region)

Based on above outcomes, the actual and forecasted plots of NA region can be shown according to Figure 5.27.

5.2.6 Fitted VAR Model for Oceania Region Glazed Tiles Imports

Thus, based on above outcome, it can be recommended that the VAR(2) model is suitable to forecast the export potential of ceramic glazed tiles to the Oceania region. The derived model can be represented as shown below:

OCEANIA(t) = C(6)*NA(t-1) + C(7)*NA(t-2) + C(8)*OCEANIA(t-1) + C(9)*OCEANIA(t-2) + C(10)

$$X_t = C(6)X_{t-1} + C(7)X_{t-2} + C(8)Z_{t-1} + C(9)Z_{t-2} + C(10)$$
$$X_t = 0.042375X_{t-1} + 0.016762X_{t-2} + 0.359217Z_{t-1} - 0.065739Z_{t-2} + 74382771$$

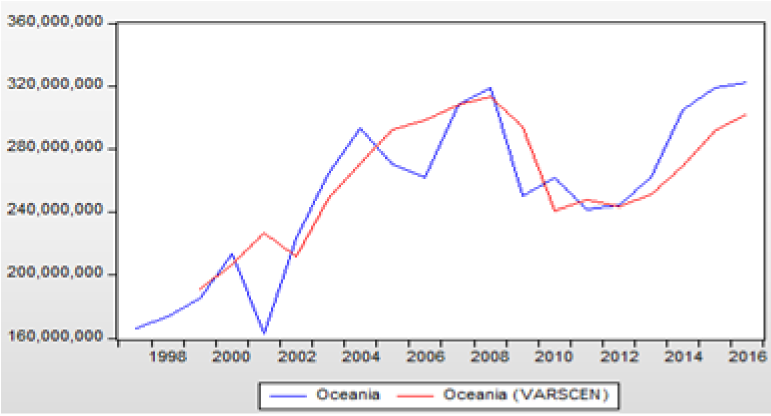


Figure 5.28: Actual vs Forecast (Oceania region)

Based on above outcomes, the actual and forecasted plots of Oceania region can be shown according to Figure 5.28.

5.3 Multivariate Forecasting for Regions Where Opportunity is Low

Similar to an earlier approach, multivariate forecasting methods have been applied over low potential markets which represents the SA region and EU. According to the current Sri Lanka export figures these markets have not highly developed due to certain other factors which were described in the introductory stage. However, knowing the movement of these markets is also highly beneficial for making decisions at the strategic level.

5.3.1 Optimal Lag Length

In order to determine the appropriate number of lags, the lag length selection criterion was checked. Through AIC and SC information criteria, the optimal lag length can be determined. Table 5.9 indicates the results of the above mentioned likelihood ratio tests. The greatest statistic is the number of lags recommended by the selected criteria. Here we found that all information criterions which are AIC, SC and HQ indicate the optimal length is lag 1.

Table 5.9: lag length selection criterion

VAR Lag Order Selection Criteria
Endogenous variables: EU SA
Exogenous variables: C
Date: 07/16/18 Time: 00:45
Sample: 1997 2016
Included observations: 18

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-766.0681	NA	3.96e+34	85.34090	85.43983	85.35454
1	-737.9673	46.83471*	2.74e+33*	82.66303*	82.95982*	82.70395*
2	-735.8425	3.069133	3.46e+33	82.87139	83.36604	82.93959

All the variables are non stationary and they can be made stationary at the same level of difference. Thus, cointegration tests can be applied for the optimal lag length found above.

5.3.2 Cointegration Test

Similar to the earlier cases cointegration test has carried over identified optimal lag length. If we found a significant cointegration or long run association we can determine the VEC type or cointegrated VAR model. If not, we can determine the VAR type model.

Table 5.10: Cointegration rank test

Series: EU SA
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

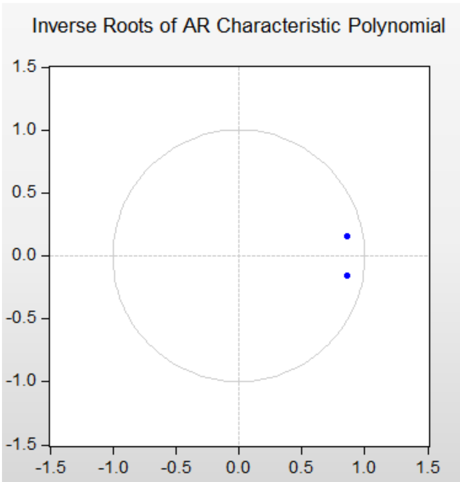
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.377495	11.30904	15.49471	0.1932
At most 1	0.142965	2.776970	3.841466	0.0956

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

According to Table 5.10 of Trace test of cointegration accept the null hypothesis of no cointegration equation because Trace statistics are less than critical values and are not significant (p=0.09).Hence we can say that there is no significant long run association ship between North American and Oceania regions. This means that a VAR type of model can be used in forecasting. Therefore, VAR(1) model run for optimal lag length and to initially check the stability of the model as shown below.

5.3.3 Stability of Model

If modulus values are less than 1, it is said to be a stable process (Lutkepohl, 2006). A stable process is one that will not deviate to infinity at vital fact is that stability indicates stationarity and it is adequate to test for stability to ensure that a VAR process is both stable and stationary.



Roots of Characteristic Polynomial
Endogenous variables: EU SA
Exogenous variables: C
Lag specification: 1 1
Date: 07/16/18 Time: 00:47

Root	Modulus
0.860129 - 0.156902i	0.874323
0.860129 + 0.156902i	0.874323

No root lies outside the unit circle.
VAR satisfies the stability condition.

Figure 5.29: Stability of VAR model for EU & SA

According to the Figure 5.29 of inverse roots of characteristics polynomials, we found that all the roots are lye within a unit root circle and all the modulus values are less than one. Thus derived VAR(1) model satisfies the stability condition for moderate potential markets.

Table 5.11:Wald test

VAR Lag Exclusion Wald Tests
Date: 07/16/18 Time: 00:48
Sample: 1997 2016
Included observations: 19

Chi-squared test statistics for lag exclusion:
Numbers in [] are p-values

	EU	SA	Joint
Lag 1	32.47369 [0.0000]	105.0171 [0.0000]	143.5327 [0.0000]
df	2	2	4

Moreover, to further investigate the lag exclusion Wald test was run as per Table 5.11 and it was found that all the variables at 1stlag was jointly significant and should be therefore included in the model.

5.3.4 VAR Model Estimation –EU & SA Region Ceramic Glazed Tiles Imports

Dependent Variable: EU
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 07/16/18 Time: 00:49
Sample (adjusted): 1998 2016
Included observations: 19 after adjustments
EU = C(1)*EU(-1) + C(2)*SA(-1) + C(3)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.852086	0.152082	5.602817	0.0000
C(2)	-0.612489	0.536830	-1.140936	0.2707
C(3)	8.12E+08	5.60E+08	1.450323	0.1663

R-squared	0.669924	Mean dependent var	3.91E+09
Adjusted R-squared	0.628665	S.D. dependent var	8.18E+08
S.E. of regression	4.99E+08	Akaike info criterion	43.03704
Sum squared resid	3.98E+18	Schwarz criterion	43.18616
Log likelihood	-405.8519	Hannan-Quinn criter.	43.06228
F-statistic	16.23685	Durbin-Watson stat	1.821756
Prob(F-statistic)	0.000141		

(a)

Dependent Variable: SA
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 07/16/18 Time: 00:51
Sample (adjusted): 1998 2016
Included observations: 19 after adjustments
SA = C(4)*EU(-1) + C(5)* SA(-1) + C(6)

	Coefficient	Std. Error	t-Statistic	Prob.
C(4)	0.040299	0.027772	1.451094	0.1661
C(5)	0.868173	0.098030	8.856169	0.0000
C(6)	-90833487	1.02E+08	-0.887918	0.3877

R-squared	0.867787	Mean dependent var	3.73E+08
Adjusted R-squared	0.851261	S.D. dependent var	2.36E+08
S.E. of regression	91076129	Akaike info criterion	39.63623
Sum squared resid	1.33E+17	Schwarz criterion	39.78535
Log likelihood	-373.5442	Hannan-Quinn criter.	39.66147
F-statistic	52.50856	Durbin-Watson stat	2.310064
Prob(F-statistic)	0.000000		

(b)

Figure 5.30: model coefficients and adequateness, (a)-EU region (b)-SA region

According to the output of Figure 5.30a, though individual coefficients do not seem to be significant we can observe that the model seems significant due to F=16.23(p=0.000). This reflects those coefficients are cause jointly significant. Further R squared value represents that model capable to explain 67% of the variability and model seems adequate. Similarly, the output of Figure 5.30b shows that only C(5) coefficient which 1stlag of SA region is individually significant. Other coefficients seem jointly significant due to F=52.5(p=0.000). R squared value indicates that the model is capable of explaining 86% of the variability and the model seems adequate.

Date: 07/16/18 Time: 00:51
Sample: 1997 2016
Included observations: 19

	AC	PAC	Q-Stat	Prob
1	0.278	0.278	1.7082	0.191
2	0.098	0.023	1.9349	0.380
3	0.115	0.089	2.2635	0.520
4	-0.014	-0.076	2.2685	0.687
5	0.104	0.130	2.5793	0.765
6	-0.241	-0.345	4.3639	0.628
7	-0.224	-0.063	6.0347	0.536
8	-0.137	-0.088	6.7110	0.568
9	-0.145	0.001	7.5518	0.580
10	-0.114	-0.114	8.1327	0.616
11	-0.153	-0.006	9.2989	0.594
12	-0.059	-0.044	9.4971	0.660

(a)

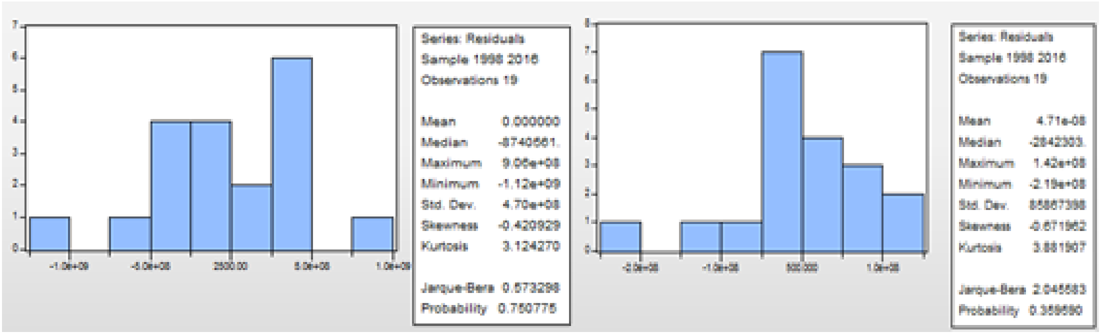
Date: 07/16/18 Time: 00:49
Sample: 1997 2016
Included observations: 19

	AC	PAC	Q-Stat	Prob
1	-0.121	-0.121	0.3225	0.570
2	0.297	0.287	2.3933	0.302
3	-0.158	-0.108	3.0144	0.389
4	-0.151	-0.285	3.6214	0.460
5	-0.160	-0.140	4.3539	0.500
6	-0.097	-0.007	4.6424	0.590
7	-0.122	-0.121	5.1391	0.643
8	-0.033	-0.131	5.1775	0.738
9	0.011	-0.015	5.1820	0.818
10	-0.025	-0.079	5.2104	0.877
11	-0.067	-0.225	5.4313	0.908
12	0.042	-0.048	5.5313	0.938

(b)

Figure 5.31:Correlagram of residuals, (a)-EU region (b)-SA region

The correlogram of squared residuals for both EU(Figure 5.31a) & SA(Figure 5.31b) models confirm the white noise of residuals.



(a) (b)

Figure 5.32: Jarque Berra test for residuals, (a)-EU region (b)-SA region

As shown in Figure 5.32(a), the JB test is not significant (p=0.75) for the EU region and as per Figure 5.32(b) JB test is not significant (p=0.35) for SA region. This confirms the residuals are normally distributed.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.227740	Prob. F(2,14)	0.7992
Obs*R-squared	0.598673	Prob. Chi-Square(2)	0.7413

(a)

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.248602	Prob. F(2,14)	0.3170
Obs*R-squared	2.876056	Prob. Chi-Square(2)	0.2374

(b)

Figure 5.33:Breusch Godfrey LM test, (a)-EU region(b)-SA region

According to the Breusch Godfrey LM test, no serial correlations are present in both EU and SA series. Figure5.33a (Obs R sq=0.59, p=0.74) indicates EU region and Figure 5.33b (Obs R sq=2.87, p=0.23) indicates SA region.

Heteroskedasticity Test: ARCH

F-statistic	0.251741	Prob. F(1,16)	0.6227
Obs*R-squared	0.278822	Prob. Chi-Square(1)	0.5975

(a)

Heteroskedasticity Test: ARCH

F-statistic	1.375821	Prob. F(1,16)	0.2580
Obs*R-squared	1.425243	Prob. Chi-Square(1)	0.2325

(b)

Figure 5.34:Heterokedasticity test for ARCH effect, (a)-EU region (b)-SA region

The Heteroskedasity test concludes that there is no ARCH effects in the model forthe EU region as indicated by Figure 5.34a (Obs R sq=0.27, p=0.59) and SA region model which is indicated in Figure 5.34b(Obs R sq=1.425, p=0.23).

5.3.5 Fitted VAR Model for EU Region Glazed Tiles Imports

Thus based on the above outcome, it can be recommended that the VAR (1) model is suitable to forecast the export potential of ceramic glazed tiles to EU region. The derived model can be presented as shown below:

EU(t) = C(1)*EU(t-1) + C(2)*SA(t-1) + C(3)

$$X_t = C(1)X_{t-1} + C(2)Z_{t-1} + C(3)$$
$$X_t = 0.852086X_{t-1} - 0.612489Z_{t-1} + 8.12E8$$

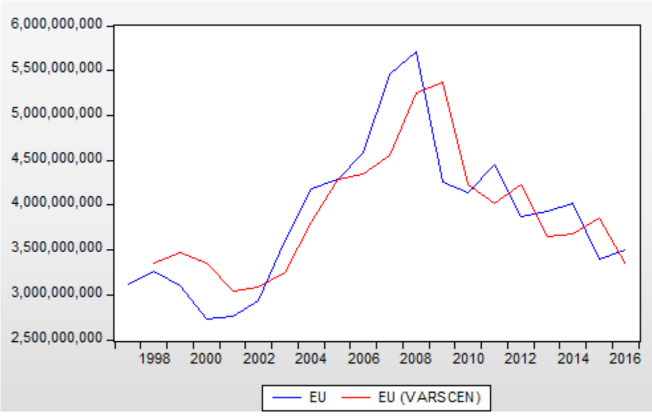


Figure 5.35:Actual vs Forecast (EU region)

Based on above outcomes, the actual and forecasted plots of EU region can be shown according to Figure 5.35.

5.3.6 Fitted VAR Model for SA Region Glazed Tiles Imports

Thus based on above outcome, it can be recommended the VAR(1) model is suitable to forecast the export potential of ceramic glazed tiles to the SA region. The derived model can be represented as shown below:

SA(t) = C(4)*EU(t-1) + C(5)*SA(t-1) + C(6)

$$Z_t = C(4)Z_{t-1} + C(5)X_{t-1} + C(6)$$

$$X_t = 0.040299X_{t-1} + 0.868173Z_{t-1} - 90833487$$

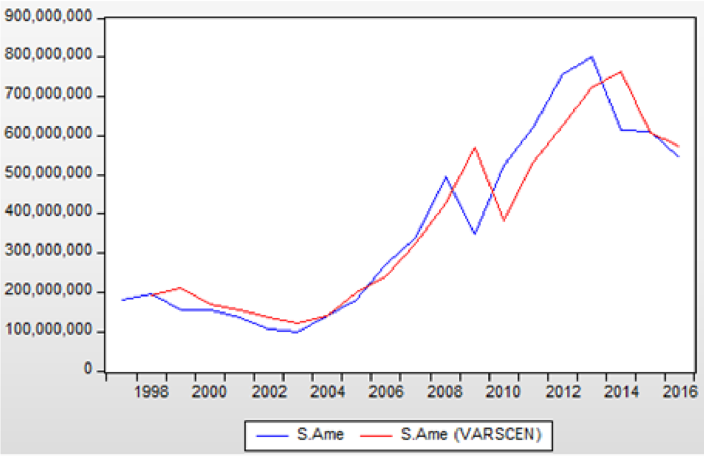


Figure 5.36:Actual vs Forecast (SA region)

Based on above outcomes, the actual and forecasted plots of SA region can be shown according to Figure 5.36.

5.4 Forecast Evaluation and Comparison

Table 5.12: Model evaluation of low and moderate opportunity markets

Low opportunity Markets				Moderate opportunity Markets			
Region	Model	MAPE	Theil Inequality coef.	Region	Model	MAPE	Theil Inequality coef.
EU	VAR(1)	9.2914	0.0576	NA	VAR(2)	6.5218	0.0376
SA	VAR(1)	14.79	0.096	Oceania	VAR(2)	7.55508	0.0483

According to Table 5.12, low and moderate markets VAR models are at quite acceptable levels as Theil inequality coefficient is quite low.

Table 5.13:Forecast and Validation –moderate opportunity markets

Region	Year	Observation	Forecast	Error %
NA	2017	1,918,780,900	1,958,387,040	2%
	2018	1,913,780,937	1,043,969,418	45%
	2019		1,095,170,014	
	2020		1,876,476,466	
	2021		2,229,831,234	
	2022		2,030,268,697	
	2023		1,998,452,798	
	2024		2,370,866,633	
Oceania	2017	458,298,001	774,006,899	69%
	2018	501,344,013	661,345,616	32%
	2019		361,650,352	
	2020		425,567,361	
	2021		700,545,036	
	2022		788,837,327	
	2023		702,272,444	
	2024		701,774,442	

As per the Table 5.13, in 2017 and 2018 observed figured were checked over forecasted figures for validation purposes. Other than 2017, the Oceania region other forecasted figures indicate reasonable error percentages. According to the models, the Oceania region market expects to further grow by 2024 which is about 10% CAGR (BM 2.8%). There is an opportunity to expand the current business in this region. By 2024 NA market is expected to grow only by 0.3% CAGR (BM 20.4%).Though growth rate is smaller in NA region, there is good opportunity to expand current business due to BM is quite larger.

Table 5.14: Forecast and Validation –low opportunity markets

Region	Year	Observation	Forecast	Error %
SA	2017	500,632,954	297,243,184	41%
	2018	581,632,954	303,612,760	48%
	2019		718,968,354	
	2020		506,352,881	
	2021		170,301,089	
	2022		556,856,487	
	2023		1,092,046,480	
	2024		1,050,818,933	

Europe	2017	3,431,500,693	3,464,701,409	1%
	2018	3,881,500,693	3,943,641,756	2%
	2019		3,608,074,269	
	2020		3,277,282,364	
	2021		3,038,132,850	
	2022		2,336,645,124	
	2023		2,609,868,124	
	2024		2,514,879,634	

As per the Table 5.14, in 2017 and 2018 observed figures were checked over forecasted figures for validation purposes. All the error percentages are quite reasonable. The SA market is expected to grow by 8% CAGR(BM 4.8%) as many developing countries exists. Due to geographic distance, existing larger manufactures and buying power in this region makes it harder to reach this market. The EU region is expected to further decline the market by-4% CAGR(BM 30.8%) as most of EU countries were developed and less infrastructure developments will take place in coming years.

Table 5.15: Univariate and multivariate models comparison in high opportunity markets

High opportunity Markets Comparison						
Region	Univariate Model			Multivariate Model		
	Model	**MAPE**	**Theil Inequality coef.**	**Model**	**MAPE**	**Theil Inequality coef.**
ME	ARIMA(1,2,0)	0.545	0.0034	VAR(1)	0.387	0.0024
Africa	ARIMA(1,2,0)	0.707	0.0048	VAR(1)	0.513	0.0033
Asia	ARIMA(1,2,0)	0.624	0.0043	VAR(1)	0.390	0.0027

To evaluate the best fit model in terms of univariate and multivariate models, the mean absolute percentage error and Theil inequality coefficient have been reviewed in markets with high opportunity. According to the summary of Table 5.15, when compared one to one, irrespective of these three regions, it was found that the mean absolute percentage error and Theil inequality coefficient statistics which indicates the measure of the distance of the true from the forecasted values are lower in multivariate model.

Table 5.16: Forecast and Validation –high opportunity markets

Region	Year	Observation	Forecast	Error %
ME	2017	1,922,150,600	2,008,086,607	4%
	2018	1,852,142,695	2,016,444,987	9%
	2019		2,025,034,081	
	2020		2,033,399,897	
	2021		2,041,298,046	
	2022		2,048,607,837	
	2023		2,055,283,201	
	2024		2,061,322,751	
Africa	2017	1,302,445,990	1,442,446,631	11%
	2018	1,362,592,749	1,480,945,471	9%
	2019		1,510,562,407	
	2020		1,533,817,867	
	2021		1,552,436,555	
	2022		1,567,614,327	
	2023		1,580,188,052	
	2024		1,690,749,580	
Asia	2017	2,064,064,930	2,239,405,545	8%
	2018	2,087,908,826	2,279,957,065	9%
	2019		2,311,580,880	
	2020		2,336,680,333	
	2021		2,356,966,055	
	2022		2,373,641,876	
	2023		2,387,556,639	
	2024		2,399,314,723	

As per the Table 5.16, in 2017 and 2018 observed figures were checked over forecasted figures for validation purposes. Lower error percentages indicate that the model suits well. According to the VAR model, these regions are expected to grow by 6%(BM 8.3%), 3%(BM 17.1%) and 2%(BM 15.8%) of CAGR consecutively Africa, Asia and ME by 2024. So there is a good opportunity in terms of exports. Current imports Figures in these three regions highlight that Sri Lanka has not focused to penetrate sufficiently into these regions.

5.5 Summary of Chapter 5

Markets which are recognized as high opportunity in chapter 4 were further reviewed using multivariate techniques. Similarly, other regions such as NA, Oceania, SA and EU could also be forecasted using VAR models. Furthermore, the study compared high opportunity markets univariate and multivariate model outcomes and figured out that the VAR approach gives better results than ARIMA models due to low MAPE and low Theil inequality coefficients and the VAR models can be recommended to forecast regional ceramic glazed tiles imports markets.

CHAPTER 6

CONCLUSIONS, RECOMMENDATIONS& FUTURE WORKS

6.1 Conclusions

Extracted secondary data for worldwide ceramic glazed tile trading from United Nations statistical division were analysed under simple tabular formats and graphs. Based on 2016 Sri Lankan export figures, it is evident that Sri Lanka is mainly focused on a few markets such as Australia, Canada and the United States. When compared regional statistics, it was found that there seems to be a good opportunity in African, Middle East and Asian regions. Here it was attempted to map these markets using univariate and multivariate forecasting methods to see the movement of coming years and to identify true export potential. Then, other regions such as North America, South America, Oceania and Europe were also analysed using multivariate techniques to realize the movements in coming years.

African, Middle East and Asian regional statistics of ceramic glazed tile imports were analysed using univariate and multivariate analysis techniques. Irrespective of regions, it was found that ARIMA (1,2,0) model is better among univariate models. However, compared to MAPE and Theil inequality coefficients it was found that the VAR(1) model seems more adequate to forecast these regions potential. According to the model developed we can expect to grow the imports market by 6%, 3% and 2% of CAGR consecutively Africa, Asia and Middle East by 2024. Other regions also analysed using VAR models and found that the Oceania region is going to further grow the import market by 10% CAGR. North America is expected to grow by 0.3% CAGR. The South American region is expected to grow by 8% CAGR and the EU is expected to experience a market decline.

6.2 Recommendations

African, Middle East and Asian regional forecasted output of import market growth indicates that there is untapped export potential. Especially companies can focus to develop business in the African region among these three regions. Among other regions, it was found that the Oceania region is going to further grow the imports market by 10% CAGR by 2024 and there is more export opportunity to expand current business in this region and penetrate deeper in to the market. The North American region is expected to grow only by 0.3% and the EU region is expected to decline. These figures indicate that there is no use of focusing on these regions. Though the South American region is expected to grow by 8% CAGR, geographic location, presence of larger manufacturers such as Brazil and less buying power of Latin Americans in this particular region creates lesser possibilities to access these markets.

6.3 Future Works

The ceramic glazed tiles industry has a vast history and research studies related to the industry within Sri Lanka are very rare. In this paper, we basically focused on developing a model to see how export potential would look like in coming years in respect to Sri Lankan business. Here we mainly focused on Africa, ME and Asian markets as constructions and infrastructure are expected to increase in these three regions in the coming years. Sri Lankan export figures also confirmed that currently these markets have not been tapped sufficiently. Ceramic has become a more fashionable industry which creates trends from time to time. Finding a method to tap market trends can be highly beneficial in future studies. Also with the same kind of data we can add more variables such as economical indexes and try to find out better forecasting models. The latest version of E views having the facility of principal components, complex VAR models such as, panel VAR can be used in such cases. Also, pooled variables might be another technique that can be used for further analysis.

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APPENDIX 1

LIST OF COUNTRIES

AFRICA	M.EAST	EUROPE	OCEANIA	N. AMERICA	S. AMERICA	ASIA
Algeria	Bahrain	Albania	Australia	Antigua and Barbuda	Argentina	Afghanistan
Angola	Cyprus	Andorra	Fiji	Bahamas	Bolivia	Bangladesh
Benin	Egypt	Armenia	Kiribati	Barbados	Brazil	Bhutan
Botswana	Iran	Austria	Marshall Islands	Belize	Chile	Brunei
Burkina	Iraq	Azerbaijan	Micronesia	Canada	Colombia	Burma (Myanmar)
Burundi	Israel	Belarus	Nauru	Costa Rica	Ecuador	Cambodia
Cameroon	Jordan	Belgium	New Zealand	Cuba	Guyana	China
Cape Verde	Kuwait	Bosnia and Herzegovina	Palau	Dominica	Paraguay	East Timor
Central African Republic	Lebanon	Bulgaria	Papua New Guinea	Dominican Republic	Peru	India
Chad	Oman	Croatia	Samoa	El Salvador	Suriname	Indonesia
Comoros	Qatar	Czech Republic	Solomon Islands	Grenada	Uruguay	Japan
Congo	Saudi Arabia	Denmark	Tonga	Guatemala	Venezuela	Kazakhstan
Congo, Democratic Republic of	Syria	Estonia	Tuvalu	Haiti	Mexico	Korea, North
Djibouti	Turkey	Finland	Vanuatu	Honduras	Trinidad and Tobago	Korea, South
Equatorial Guinea	United Arab Emirates	France		Jamaica		Kyrgyzstan
Eritrea	Yemen	Georgia		United States		Laos
Ethiopia		Germany		Panama		Malaysia
Gabon		Greece		Nicaragua		Maldives
Gambia		Hungary		Saint Kitts and Nevis		Mongolia
Ghana		Iceland		Saint Lucia		Nepal
Guinea		Ireland		Saint Vincent and the Grenadines		Pakistan
Guinea-Bissau		Italy				Philippines
Ivory Coast		Latvia				Russian Federation
Kenya		Liechtenstein				Singapore
Lesotho		Lithuania				Sri Lanka
Liberia		Luxembourg				Tajikistan
Libya		Macedonia				Thailand
Madagascar		Malta				Turkmenistan
Malawi		Moldova				Uzbekistan
Mali		Monaco				Vietnam
Mauritania		Montenegro				
Mauritius		Netherlands				
Morocco		Norway				
Mozambique		Poland				
Namibia		Portugal				
Niger		Romania				
Nigeria		San Marino				
Rwanda		Serbia				
Sao Tome and Principe		Slovakia				
Senegal		Slovenia				
Seychelles		Spain				
Sierra Leone		Sweden				
Somalia		Switzerland				
South Africa		Ukraine				
South Sudan		United Kingdom				
Sudan		Vatican City				
Swaziland						
Tanzania						
Togo						
Tunisia						
Uganda						
Zambia						
Zimbabwe						

APENDIX II

OBSERVATIONS, FORECASTED AND ERROR PERCENTAGES

Middle East

Year	M.East Obs	ARIMA Forecasted in US$	ARIMA % Error converted series	VAR Forecasted in US$	VAR % Error converted series
1997	150,533,486				
1998	219,138,621	210,581,438	3.905%	209,793,355	4.265%
1999	258,385,528	301,031,416	16.505%	288,436,444	11.630%
2000	360,028,724	342,628,571	4.833%	392,967,546	9.149%
2001	414,918,265	453,016,940	9.182%	436,281,746	5.149%
2002	526,798,232	511,946,542	2.819%	552,803,553	4.936%
2003	704,775,341	626,815,957	11.062%	614,010,985	12.878%
2004	785,784,071	799,907,315	1.797%	729,881,637	7.114%
2005	862,452,583	877,771,742	1.776%	897,919,083	4.112%
2006	982,153,213	947,248,596	3.554%	973,734,972	0.857%
2007	1,115,843,881	1,081,873,105	3.044%	1,039,859,712	6.810%
2008	1,367,614,175	1,217,866,748	10.950%	1,173,286,710	14.209%
2009	1,149,095,854	1,426,782,418	24.166%	1,302,873,771	13.383%
2010	1,366,942,016	1,276,986,356	6.581%	1,485,699,383	8.688%
2011	1,441,691,797	1,489,199,913	3.295%	1,363,705,649	5.409%
2012	1,530,354,712	1,520,308,841	0.656%	1,559,264,801	1.889%
2013	1,780,795,077	1,608,829,517	9.657%	1,580,103,167	11.270%
2014	1,969,532,931	1,832,017,912	6.982%	1,663,235,936	15.552%
2015	1,586,897,878	1,996,171,418	25.791%	1,858,249,450	17.099%
2016	1,792,150,695	1,642,010,033	8.378%	2,000,792,708	11.642%
2017	**1,922,150,600**	1,587,650,100	17.402%	2,008,086,607	4.471%
2018	**1,852,142,695**	1,680,550,158	9.265%	2,016,444,987	8.871%

Africa

Year	Africa Obs	ARIMA Forecasted in US$	ARIMA % Error converted series	VAR Forecasted in US$	VAR % Error converted series
1997	132,405,380				
1998	182,874,605	161,041,124	11.939%	161,415,862	11.734%
1999	147,535,609	180,629,502	22.431%	166,739,165	13.016%
2000	163,409,115	160,097,321	2.027%	190,305,474	16.460%
2001	182,837,885	187,606,151	2.608%	180,820,115	1.104%
2002	211,143,194	210,802,332	0.161%	219,758,998	4.081%
2003	239,228,155	250,761,025	4.821%	247,549,902	3.479%
2004	282,298,971	300,620,549	6.490%	298,064,678	5.585%
2005	313,560,285	357,298,653	13.949%	366,012,263	16.728%
2006	477,847,425	408,306,539	14.553%	428,451,310	10.337%
2007	616,108,653	541,638,636	12.087%	486,254,885	21.076%
2008	583,719,487	661,472,921	13.320%	610,703,480	4.623%
2009	781,945,219	707,545,485	9.515%	726,728,989	7.061%
2010	995,397,712	724,527,927	27.212%	809,639,862	18.662%
2011	869,005,042	900,529,373	3.628%	769,272,112	11.477%
2012	1,048,514,902	931,083,316	11.200%	940,188,845	10.331%
2013	1,138,145,934	1,084,966,445	4.672%	998,000,073	12.314%
2014	1,252,754,635	1,189,497,866	5.049%	1,133,038,992	9.556%
2015	992,134,090	1,321,325,328	33.180%	1,255,104,795	26.506%
2016	945,703,764	1,104,807,780	16.824%	1,391,272,097	47.115%
2017	**1,202,445,990**	833,526,786	30.681%	1,442,446,631	19.959%
2018	**1,262,592,749**	689,216,335	45.413%	1,480,945,471	17.294%

Asia

Year	Asia Obs	ARIMA Forecasted in US$	ARIMA % Error converted series	VAR Forecasted in US$	VAR % Error converted series
1997	640,311,112				
1998	453,823,917	437,845,402	17.98%	437,377,484	3.624%
1999	379,410,072	425,315,412	57.82%	405,822,114	6.961%
2000	407,664,568	393,789,715	17.47%	446,970,790	9.642%
2001	441,045,490	452,242,668	12.60%	437,747,908	0.748%
2002	500,458,644	496,355,279	4.11%	516,847,983	3.275%
2003	572,197,311	575,073,386	2.49%	568,684,906	0.614%
2004	690,789,630	676,340,721	10.39%	662,101,906	4.153%
2005	816,324,468	783,562,147	19.96%	786,184,043	3.692%
2006	1,147,118,353	886,736,704	123.42%	888,816,721	22.517%
2007	901,912,350	1,055,212,211	76.13%	983,294,613	9.023%
2008	1,223,958,886	1,214,532,269	3.69%	1,156,221,072	5.534%
2009	1,033,105,954	1,341,289,540	125.78%	1,316,680,494	27.449%
2010	1,226,627,988	1,225,180,142	0.56%	1,457,408,113	18.814%
2011	1,524,561,919	1,447,209,300	24.63%	1,356,219,333	11.042%
2012	1,757,855,012	1,607,063,019	42.13%	1,583,401,411	9.924%
2013	1,834,257,697	1,801,257,558	8.51%	1,686,178,961	8.073%
2014	2,019,845,254	1,937,886,507	19.33%	1,851,681,727	8.326%
2015	1,924,461,483	2,117,845,626	44.79%	2,014,292,667	4.668%
2016	1,947,231,066	1,888,966,682	14.20%	2,186,679,898	12.297%
2017	**2,064,064,930**	2,011,352,870	12.06%	2,239,405,545	8.495%
2018	**2,087,908,826**	1,970,606,768	26.94%	2,279,957,065	9.198%

NA & Oceania

Year	NA obs	NA Forecast	Err %	Oceania Obs	Oceania Forecast	Err %
1997	966,752,503			166,110,109		
1998	1,156,002,768			173,719,853		
1999	1,365,229,159	1,455,553,076	6.62%	185,403,730	191,055,950	3.05%
2000	1,535,679,193	1,617,508,073	5.33%	213,924,666	206,790,868	3.33%
2001	1,597,866,644	1,703,005,230	6.58%	162,872,151	226,997,781	39.37%
2002	1,830,261,739	1,779,119,893	2.79%	223,819,028	212,276,140	5.16%
2003	2,017,616,133	1,890,675,263	6.29%	263,759,235	248,415,567	5.82%
2004	2,277,834,647	2,077,259,263	8.81%	293,153,447	270,590,622	7.70%
2005	2,535,477,851	2,363,587,881	6.78%	270,257,752	292,691,024	8.30%
2006	2,706,989,710	2,623,055,563	3.10%	262,066,559	297,813,503	13.64%
2007	2,364,686,006	2,637,599,111	11.54%	307,756,567	307,962,587	0.07%
2008	2,015,029,270	1,973,131,483	2.08%	319,292,775	313,283,298	1.88%
2009	1,504,722,349	1,815,357,075	20.64%	250,255,224	293,869,351	17.43%
2010	1,671,993,773	1,444,379,795	13.61%	261,390,589	240,826,399	7.87%
2011	1,686,265,585	1,885,664,900	11.82%	241,821,947	247,899,508	2.51%
2012	1,808,900,820	1,828,839,245	1.10%	244,370,056	243,546,598	0.34%
2013	2,036,881,068	1,945,913,937	4.47%	261,618,926	251,184,259	3.99%
2014	2,149,177,640	2,165,554,564	0.76%	304,894,166	268,929,089	11.80%
2015	2,289,842,688	2,153,588,263	5.95%	319,128,726	291,920,233	8.53%
2016	2,313,780,937	2,348,442,597	1.50%	322,298,843	302,031,609	6.29%
2017	1,918,780,900	1,958,387,040	2.06%	458,298,001	774,006,899	68.89%
2018	1,913,780,937	1,043,969,418	45.45%	501,344,013	661,345,616	31.91%

SA & EU

Year	SA Obs	SA forecast	Err %	EU Obs	EU Forecast	Err %
1997	182,106,267			3,108,689,831		
1998	197,798,041	192,543,786	2.66%	3,260,463,491	3,349,816,079	2.74%
1999	155,466,863	212,283,309	36.55%	3,097,455,245	3,469,529,209	12.01%
2000	154,127,243	168,963,425	9.63%	2,733,726,435	3,356,559,597	22.78%
2001	134,756,885	153,142,449	13.64%	2,766,913,311	3,047,451,965	10.14%
2002	107,990,634	137,663,025	27.48%	2,936,177,807	3,087,594,165	5.16%
2003	100,716,240	121,246,495	20.38%	3,598,367,888	3,248,216,071	9.73%
2004	138,774,442	141,616,745	2.05%	4,184,719,226	3,816,914,290	8.79%
2005	181,479,451	198,287,304	9.26%	4,284,485,108	4,293,225,669	0.20%
2006	269,672,353	239,383,126	11.23%	4,588,241,167	4,352,078,396	5.15%
2007	341,814,264	328,190,944	3.99%	5,463,292,982	4,556,887,401	16.59%
2008	493,931,292	426,086,444	13.74%	5,709,010,026	5,258,320,436	7.89%
2009	348,885,292	568,052,552	62.82%	4,257,204,792	5,374,522,383	26.25%
2010	525,302,564	383,621,017	26.97%	4,143,610,510	4,226,298,949	2.00%
2011	620,507,881	532,204,012	14.23%	4,454,217,500	4,021,453,197	9.72%
2012	757,310,431	627,375,908	17.16%	3,876,995,387	4,227,804,754	9.05%
2013	800,632,954	722,882,665	9.71%	3,932,432,061	3,652,171,926	7.13%
2014	615,384,074	762,728,168	23.94%	4,015,739,240	3,672,874,146	8.54%
2015	609,306,572	605,257,264	0.66%	3,394,271,663	3,857,321,954	13.64%
2016	542,607,501	574,936,337	5.96%	3,503,217,439	3,331,500,693	4.90%
2017	500,632,954	297,243,184	40.63%	3,431,500,693	3,464,701,409	0.97%
2018	581,632,954	303,612,760	47.80%	3,881,500,693	3,943,641,756	1.60%