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ISTANBUL AYDIN UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

MULTIVARIATE FORECASTING OF STEEL PRICES

MASTER'S THESIS

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Department of Business
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Thesis Advisor: Asst. Prof. Dr. Uğur ŞENER

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DECLARATION

I hereby declare with respect that the study "**Multivariate Forecasting of Steel Prices**", which I submitted as a Master thesis, is written without any assistance in violation of scientific ethics and traditions in all the processes from the project phase to the conclusion of the thesis and that the works I have benefited are from those shown in the Bibliography. (…/…/2020)

Kaveh Ahmadi Adli

FOREWORD

I owe my deepest gratitude to my supervisor Asst. Prof. Uğur Şener. Without his enthusiasm, encouragement, invaluable support, and constant optimism, this thesis would hardly have been completed. I would like to extend my sincere thanks to my parents and my sister for their continuous support and encouragement during all phases of my life. A very special word of thanks goes to my wife, who never let me down.

December, 2020 Kaveh Ahmadi Adli

MULTIVARIATE FORECASTING OF STEEL PRICES

ABSTRACT

Steel products are the most used raw material for many industries regarding their accessibility, strength, and relatively low costs comparing to the other base metals with similar characteristics. In the fast-paced economic environment of the post-world war II era with the growing expansion of the economy in the world, steel usage and consequently, the prices of steel become an essential concern for the countries and organizations. From the first decade of the 21st century, with the launch of the online trades for steel products in the commodity markets, the importance of steel prices has become even more critical. The practice of the price series forecast is conducted by various statistical and data-driven models in the literature. However, there is a lack of investigation to find practical and user-friendly statistical models in forecasting steel prices where, besides simplicity, can perform realistic and precise forecasts. The VAR and VEC models are newly introduced models comparing to the conventional models in econometrics. While the exogeneity in the conventional models can cause several difficulties in model specifications, the VAR systems, by treating all the variables as endogenous variables, can overcome this issue. Also, the VEC model that is a particular case of the VAR model, can assess the short-run and long-run dynamics by the cointegration relations in a single model. The data in this study are ranged from Jan. 2009 to Jun. 2020. The forecast evaluation is through the out-of-sample approach, which is more compatible with the real-world setting. The results of this study suggest the dominance of the VAR model over the VEC model in the forecast horizon of 18 months attributed to a mid-term forecasting horizon.

Keywords: Cointegration, Forecast, Multivariate, Steel, VAR, VEC

ÇOK DEĞİŞKENLİ TAHMİN MODELLERİNİN ÇELİK FİYATLARINA UYGULANMASI

ÖZET

Çelik dünyada yaygın olarak bulunan, dayanıklı ve benzer özelliklere sahip diğer ana metallere göre düşük maliyetli olma gibi üstünlükleri sayesinde özellikle üretim sektöründe en çok kullanılan hammadde haline gelmiştir. İkinci dünya Savaşı sonrasında hızla gelişen ve genişleyen ekonomik ortamda, çelik kullanımı ve dolayısıyla çelik fiyatları ülkeler ve kuruluşlar için önemli bir konu haline geldi. 21. yüzyılın ilk on yılından itibaren, emtia piyasalarında çelik ürünleri için çevrimiçi ticaretin başlamasıyla birlikte, çelik fiyatlarının önemi daha da artmıştır. Gittikçe önemi artan çelik fiyat serilerinin öngörüsü, literatürdeki çalışmaları göz önunde bulundurarak, çeşitli istatistiksel ve veriye dayalı modellerle yapılmaktadır. Ancak, basitliğin yanı sıra gerçekçi ve isabetli öngörüler yapabilen çelik fiyatlarına yönelik pratik ve kullanıcı dostu olan istatistiksel modellerinin kullanımının eksikliği literatürde görülmektedir. VAR ve VEC modelleri, ekonometride geleneksel modellere kıyasla, görece yeni tanıtılan modellerdir. Geleneksel modellerdeki dışsallık, model spesifikasyonlarında çeşitli zorluklara neden olabilirken, VAR sistemleri tüm değişkenleri içsel değişken olarak ele almaktadır. Ayrıca, VAR modelinin bir varyasyonu olan VEC modeli, tek bir model kulanarak, kointegrasyon yaklaşımına dayanarak kısa vadeli ve uzun vadeli dinamiklerini aynı zamanda değerlendirebilir. Bu çalışmada Ocak 2009 ve Haziran 2020 arasındaki aylık veriler kullanılmıştır. Tahmin değerlendirmesi, gerçeksel ortamla daha uyumlu olan, örneklem dışı yaklaşımla yapılmıştır. Bu çalışmanın sonuçları, orta vadeli olarak değerlendirilen 18 aylık öngörü ufkunda, LVAR modelinin VEC modeline üstünlüğünü göstermektedir.

Anahtar Kelimeler: Çok değişkenli Öngörü Modelleri, Çelik, Kointegrasyon, VAR, VEC

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ABBREVIATIONS

ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
ECM	Error Correction Model
ECT	Error Correction Term
FEVD	Forecast Error Variance Decomposition
GDP	Gross Domestic Production
IRF	Impulse Response Function
ITC	International Trade Commission
LME	London Metal Exchange
Ln	Natural Logarithm
LVAR	VAR model on levels
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
NYMEX	New York Mercantile Exchange
OLS	Ordinary Least Square
PACF	The Partial Autocorrelation Function
PPI	Producer Price Index

RMSE Root Mean Square Error

SCI Schwarz information criterion

SSE Sum of Squared Errors

VAR Vector Autoregressive

VEC Vector Error Correction

VECM Vector Error Correction Model

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I. INTRODUCTION

A. History

Iron is the fourth element on the earth regarding redundancy, and about five percent of the earth's crust consists of iron. Initially, iron is manufactured around 2000 BC in southern Asia, which was the end of the bronze age. However, iron usage was expanded only after alloyed with carbon that has resulted in better characteristics compared to bronze. Subsequently, it is replaced by steel in mid-19th (Spoerl, 2004).

According to Verhoeven (2016), Mass scale production of steel started in the mid-19ths with the invention of the Bessemer process. New processes make it possible to produce cheaper steel. Andrew Carnegie – Industrialist – efforts to produce better quality cheap steel, lower the prices to $14 per ton in the late 19th century (Spoerl, 2004).

B. Importance of Steel and Its functions

Steel products are one of the essential intermediate commodities in the modern era, which results in economic growth and expansion. Everything we use is made of steel or steel equipment. In 2018, World crude steel production was reached an enormous amount of 1.87 billion tonnes with the apparent use of finished steel products for 1.76 billion tonnes (World Steel Association 2020). Nowadays, the usage of different types of steel products in a variety of industries such as construction, automaker, space, and aeronautics to the military, makes steel production a vital industry. Due to the high demand for steel, major labor force, and extensive facilities as national entities, the steel industry turns out to be politically and also economically significant (Jones, 2017).

Various steel applications can be seen as developed countries' foundation. Whereas economic growth is vital regarding making wealth and fulfilling the needs of people, the steel industry is among the industries which help to satisfy these conditions. According to Dobrotă & Căruntu (2013), there is a positive relationship between economic growth and the production of crude steel in the aspect of GDP per capita. Furthermore, the technological advancement of a country can be predicted by the regime of steel usage.

The importance of steel consumption in the passenger car industry can be emphasized by the official reports show that more than 65% of an ordinary new car's weight consists of steel and its components (Tilton, 1990). Referring to Bhat (2005), among the metallic materials, steel is the most widely used alloy in space exploration structures due to its excellent strength, flexibility, and low cost. Also, in the construction industry, all the buildings and structures mostly depend on steel for their rigidity.

Organization for Economic Co-operation and Development (OECD) Steel committee reported that up to 50% of steel consumption occurs in the construction industry, and the remaining half is divided almost equally between three industries: Transportation, Machinery, and Metal products. The Construction industry solely contributes to global GDP by 13% (OECD 2010).

C. Importance of Steel Price Forecasting

The prices are across the most demanding economic variables to predict (Popkin 1977). The importance of price specification in the business environment is unnegotiable, and it is the most critical factor for competitive advantage both at the corporate or country level. The Price forecasts can be used to diminish the ambiguity and help in the decision making process among organizations (Zarnowitz 1972). However, economic predictions boost assured establishment of strategies and investment plans in the long-term (Malanichev and Vorobyev 2011).

Generally, price forecasts are utilized as a tool for business activities such as budgeting, investment, risk analysis, and policymaking. Looking into the more comprehensive picture, it seems that price forecasting is the principal component of every financial planning. A proper plan, regardless of scope and duration, depends on forecasting. For emphasizing the importance of planning, General Eisenhower said: "Plans are nothing, but planning is everything."

Regarding the knowledge that the future is the expansion of the present, thus making a reliable forecast, the past and present have to be assessed precisely (Szilágyi, Varga, and Géczi-Papp 2016). Price forecast is a useful skill for major establishments for planning as well as traders and small businesses to make a profit regarding knowledge about the price fluctuations.

Xia (2000) claims that the determination of steel prices has an essential role in the formulation of economic policy in less-developed countries. Robust steel prices forecasting has tremendous importance to specify and understand the steel market behavior and, consequently, for the industry to react in advance to fluctuations.

The London Metal Exchange (LME), as the largest commodity market for metals, has begun to trade steel since 2007. Consequently, the New York Mercantile Exchange (NYMEX) started to trade steel with future contract options. In these markets, most of the trades are made by future contracts that make steel a financial asset rather than a physical asset (Arık and Mutlu 2014). Since financial assets are prone to volatility, the forecasting of steel importance becomes critical for traders.

D. Insights About the Global Steel Industry and the United States

From the global steel industry’s data, it is observed a tremendous growth rate for crude steel production in the 1950-55 period with %7.4 as a reason for industrial recovery after the world war two economic crisis. In 1979 with the reforms applied to the Chinese economy to implement free-market rules, the country’s economic growth become the fastest in the world with an average real Gross Domestic Production (GDP) of 9.5% in 2018. China has become the world's most enormous steel producer and consumer with 927.5(%51.3) and 835.4(%48.8) million tons, respectively.

In the global steel industry, the ArcelorMittal company, based in Luxembourg, is the largest steel producer in the world, with 92.5 million tons of crude steel production following 76,033 million USD sales revenue, in 2018 which solely accounts for %5 of global crude steel production (ArcelorMittal 2019).

The U.S. was the world’s second largest steel product importer with a value of 23.9 billion USD in 2019. Canada, Brazil, Mexico, and South Korea are the major exporters to the United States. Also, the U.S. is the fourth major steel producer after

China, India, and Japan, with a total production of 87.9 million metric tons. Most steel production in the U.S. is made with iron and steel scrap instead of iron ore, which makes the scrap as an essential raw material in steel making. In recent years, the uncertainty in the steel market has increased due to the trade war between China and the U.S. that hit the steel market and complications related to the Covid-19 pandemic in the world.

E. The aim and scope

The current thesis aims to develop a proper multivariate model for forecasting steel prices. For explanatory variables, previous studies are considered in addition to some new variables which might affect steel prices as well. The models being used in this study are econometric models that use statistical analysis. The *Vector Autoregression (VAR)* and *Vector Error Correction (VEC)* models, which are extensions of George Box & Jenkins (1976), univariate *Autoregressive Integrated Moving Average (ARIMA)* model are used for modeling purpose.

The forecast horizon is set to 18 months, which is equal to the average duration of future contracts in LME and NYMEX. whether in conventional markets or commodity exchanges, 18 months consider as an intermediate forecast horizon.

The upcoming chapters after chapter 1, that was the introduction, follow this structure; In chapter 2, available literature on the steel prices determination and forecasting is inquired in detail. Chapter 3 describes the methodologies that will be used for making models. Consequently, in chapter 4, data description and empirical results are included. Discussion and conclusion are fitted in chapter 6.

II. LITERATURE REVIEW

While economic forecasts play a significant role in policy decisions, the uncertainty in forecast results may lead the managers into erroneous conditions. While qualitative forecasts are relying on expert opinions and judgments, the quantitative forecast methods have developed under statistical knowledge consideration. The usage of statistical methods to model the financial and economic data which is called econometrics has an enormous part in limiting the uncertainty in forecasts. Econometrics has developed over the past decades as a result of the increasing calculation power in statistics. Also, the data classifications and preservice techniques make a significant contribution to economic and business data collections which then can be used with data-mining methods to simulate real-world conditions as well.

The globalization era which starts after world-war 2 initially, triggers the interest of the countries and companies over the world to trade internationally to boost their economic profile. However, regulating the suitable trade policy to support domestic industries while consolidating foreign trade has become a challenging task for the governments and policymakers.

China's extraordinary economic growth results in the commodity market boom around the 2000s as a result of increasing demand. Subsequent recession in 2008 which pushes commodity prices downwards to the historical lows, makes pressure on the policymakers and business owners to have a clear perspective into the future to be able to mitigate the possible risks. Thus, forecast methods are started to use widely as a practical means to forecast commodity prices in various governmental and private financial institutions

The price forecasting process of a commodity involves the assessment of its characteristics and movements along with other commodities' prices and some macroeconomic and microeconomic variables such as GDP, demand, supply, trade volume. Also, for intermediate commodities like steel which are made from other commodities as raw materials, the current and historical prices of these commodities are essential.

Like any quantitative forecast process, it begins with the process of problem definition which describes the ultimate goal of forecasting. Subsequently, the data collection process takes part to collect suitable historical data which is assumed to be useful in forecasting the variable of interest for a proper time duration regarding the frequency of the data (e.g., annual, semi-annual, quarterly, monthly).

The next step is data manipulation since the raw data is not suitable to form a statistical method usually. In this stage, the most useful data considering their duration, predictability power, and characteristics are selected and transform into the desired format. The following step is the model building process which in this step a proper model is tried to fit the data. The model fitting process can be evaluated with model fit measurements to ensure the right specifications of the model.

After forming a proper model, it can be used to conduct a forecast using the same data as used in model fit (*in-sample*) or data that is kept off the modeling process (*out-of-sample*). The out-of-sample forecast is believed to yields more realistic and reliable results.

The last step in the forecast process is evaluation of the forecast to define the accuracy which is applied by comparing the actual values of the variable of the interest and its predicted values. This can be investigated by several forecast accuracy measures depend on the type and ultimate goal of the forecast.

Various studies are made an effort to forecast commodity prices; therefore, a few of them have tried to forecast steel prices. Also, existing literature about modeling steel prices is mostly concentrated on determining the steel prices structure in the market and not to forecast. However, price determination and forecast problems are overlapped most of the time, since the model which is made for price discovery can be used for price forecast with some considerations, practically.

The forecast problem in financial series is devoted to the two main categories as univariate and multivariate models. The univariate model depends on the variable of interest's movements through time. In this manner, the forecast is performed by using the existing patterns in variables previous values which are used widely in the literature for the price forecasting process for the short-term forecast horizons. However, due to the involvement of several microeconomic and macroeconomic factors, univariate models could not forecast longer horizons efficiently.

To overcome the problem of uncertainty by interventions and shocks initiated by other variables the multivariate forecast models are used. In multivariate analysis, the forecast model uses various explanatory variables besides the previous values of the interest variable to perform a forecast. Usually, the multivariate forecast can capture better results in mid-term and long-term horizons comparing univariate models.

To conduct managerial decisions and policy-making processes in organizations, mid-term and long-term forecasts are necessary, while short-term forecasts have vital importance for the traders in commodity markets. Therefore, as reviewed from the literature, univariate forecasts are less popular for macroeconomic forecasts as country scale or large organizations due to limited ability to conduct accurate long-term forecasts. The multivariate forecast models use leading variables that are efficient in forecasting the variable of interest.

The earliest and most known model for multivariate analysis is the *Multiple Regression* model which the dependent variable regresses on the independent variable(s). The estimation method for the coefficients in this model is the *Least Squares Method (LS)*. The development of the regression models allows us to include the previous lags of the dependent variable and independent variables, as well. These models have belonged to the class of models which is popularized by George Box and Jenkins (1976) as *Dynamic Regression (DR)* or *Transfer Function (TF)* models. This class of models is also divided into several subsets and variations regarding some specifications in the modeling processes. The most essential ones are the *Distributed Lag (DL)* model and the *Autoregressive Distributed Lag (ARDL)* model. The ARDL model allows to include previous lags of the dependent variable besides the lags of the independent variables which is allowed in the DL model.

The assumption of the Exogeneity in the LS estimation method which articulates the independence of the explanatory variables with the error term becomes problematic in complex models with several explanatory variables. This difficulty is related to all variations of the DL models. The VAR model which is introduced by

Sims (1980), has overcome this issue by treating all variables as endogenous variables.

As an extensive issue in econometrics, the diversity and entanglement of the patterns in the time-series variables such as trend, unit-root, seasonal and irregular movements become complex and hard to distinguish. The problem arises where most of the econometrics models required decomposition of patterns in variables to analyze separately with multiple models. To prevail over this issue, the DL models required stationary (explained in detail in the methodology section) variables to form the model. The processes which are made to transform the non-stationary variables into stationary variables are entailed to some loss of information in the variables and have to be modeled by separate models.

Non-stationary variables are unstable in the mean due to the existence of the unit-root which by differencing the variables (subtraction of each value from the previous value) can become stationary. However, the differencing process eliminates the long-run dynamics of the variable due to removing stochastic trends in the variables. The financial variables are used to be non-stationary most of the time, and on the other hand, they need to be investigated for their long-run dynamics besides their short-run dynamics.

To overcome this dilemma, researchers suggested several models. therefore, the most successful and practical econometric models are VAR and VEC models. Engle and Granger (1987) study showed that the VAR model can handle the non-stationarity in the variables with consistent coefficient estimation. In addition, they introduced the new model based on the VAR model as the VEC model which separates the short-run and long-run dynamic of the variables by using the cointegration concept which is fully covered in the methodology section.

It is worth noting that the majority of studies used econometric models for determining and forecasting steel prices. Few recent studies used new data-driven models to assess and forecast steel prices, which the last one is back to 2015 by Liu, Wang, Zhu, & Zhang (2014).

In the following part of this chapter, firstly, a short brief is presented about the literature regarding methods and independent variables. Secondly, each of the related studies chronologically and methodologically is explained comprehensively. The more weight is given to pieces of literature that used multivariate methods to assess or forecast steel prices.

Available studies offer a variety of explanatory variables, both globally and domestically. Among the different factors mentioned in these researches, raw materials cost, demand and supply, shipments, and foreign trade are seemed to be more efficient.

The majority of authors applied econometric models using regression analysis (Harmon, 1969; Liebman, 2006; Malanichev & Vorobyev, 2011; Mancke, 1968; Richardson, 1999; Xia, 2000). Kapl & Müller (2010) utilized the *ARIMA* and *Multichannel Singular Spectrum Analysis (M-SSA)* methods. Chou (2013) used the fuzzy time series analysis while Wu & Zhu (2012) and Liu et al. (2015) used Artificial Neural Network (ANN) to forecast steel prices. The forecast horizon varies from one step ahead to the multiple steps in the above studies.

Mancke (1968), as one of the earliest studies on the steel industry, tried to find an aggregate econometric model by using a multivariate linear regression method for the U.S steel prices from 1947 to 65. Since the steel is not homogenous material for finding the aggregate model, he investigated plates, sheets, and bars as the most used steel types in the industry. For independent variables, he described firstly the average variable cost, which represents all the costs depend on the amount of product, including raw materials, direct labor, etc. Secondly, imports are divided by total domestic production as an indicator of the market structure, which shows foreign competition on domestic products. Thirdly, the capacity utilization demonstrates the indirect relativity of demand to supply. He used dummy variables to differentiate years between 1947-1958, 1959-1965, 1947-61, and 1962-65 to learn about changes in the market condition. He found out that from 1947 to 58, steel prices tended to rise independent of demand and supply. However, from 1959 to 65, this condition has not been held. The second range of dummy variables which he assessed for governments guideposts effect on steel prices, there is no evidence to support this idea.

Grossman (1986) investigated the United States steel industry between 1976 and 1983, remarking the steel import prices, which were suggested to harm the country’s steel industry employment rate. This study proved that despite the assumption was made by the International Trade Commission (ITC) that imports are the main reason for injury to the steel industry, other variables are more significant. He used several independent variables as time trend, industrial production, import prices, wages, price of energy and, price of iron ore to determine the effects on employment rate as the dependent variable in the multivariate regression. He concluded that the effect of industrial production as the indicator of changing demand is more than imports, which previously known as the main reason for damaging the steel industry.

In addition to Mancke (1968) and Grossman (1986) works in specifying the U.S. steel market, Blecker (1989) gave a comprehensive model to assess the steel industry between 1949 and 1983. In this work, the *Dynamic Regression (DR)* model was generated with steel prices as a dependent variable and cash dividends in product shipment, capacity utilization, import prices, market shares of four significant firms back at the time, overheads, and investments in the steel industry as independent variables. To avoid heteroscedasticity in the model due to outliers or omission of some variables, natural logarithm (ln) is used in regression analysis. He also tried to determine the demand quantity of the steel across the nation between 1954-83 regarding its impact on steel prices that it was included in the form of capacity utilization (CU) in the model. He ended that until the early 60's because of the stable oligopolistic structure of the industry (price leadership by significant steel producers), prices did not depend on the demand or imports but depend on target-return pricing. However, after this time, steel prices responsive to demand and import competition. From the late '60s, the demand starts to falling which, as stated in Grossman (1984), along with the growing import share, put downward pressure on steel prices.

Richardson (1999) investigated the effect of low-cost imports of steel from Eastern-European countries to the European Community (EC) between 1992-1994. After the 90s economic recession, as the start of the recovery phase, the steel demand in European countries was strengthened. The quarterly data are used for 12 years from 1981 to 1993 to form a model for steel price determination using multivariate linear regression.

A variety of explanatory variables as demand and potential supply capacity, cost structure, technology, price leadership, the exchange rate of ECU, surplus capacity, inventories, and trade protection policies are investigated regarding effects on EC steel prices. Therefore, for the final model, he used the amount of import, apparent consumption, capacity utilization rates, and relative world price for cold-rolled coil steel as independent variables and *Cold-Rolled Coil (CRC)* steel prices for the EC as a dependent variable. *R-squared* (R^2) statistics showed that independent variables explain about 74% of CRC prices. In another equation, the import penetration ratio is used by dividing imports by apparent consumption against CRC prices. From the results, the author concluded that for 1 (million tonnes) of imports, the price cut-off by 50 ECU (European Currency Unit).

The master thesis by Xia (2000) gave insights about different factors other than demand and supply in determining steel prices in China from 1978 to1998. It is claimed that back in 20th-century, steel prices had been controlling by the government until 1993; hence the prices did not become sensitive to demand and supply. Five macroeconomic variables are introduced as explanatory variables, the Consumer Price Index (CPI), General National Product (GNP), which is the value of all finished goods and services in a country by its nationals in a given time period, exchange rate, interest rate, and the ratio of Import to Export of the country. The multivariate hedonic regression model with a lagged dependent variable as dummy variables. the data are transformed by natural logarithm (ln) to reduce the effect of the outliers. The result of empirical processes showed that only the ratio of import to export has a significant relation with the steel prices. Also, R-squared (R^2) for this study explains about 60% of steel prices, which is not a satisfactory result. The research concluded that because of the manipulation of governments on the steel prices and lack of the equilibrium market price, all the factors except the ratio of the import to the export, show non-significant relations with steel prices. Therefore, it suggested that the model might be more suitable for countries with a free market.

Liebman (2006) is the most completed work done to investigate the U.S. steel industry. Following the previous studies, also Liebman studied the impact of safeguard tariffs on the steel industry by making the inclusive model for the steel industry. He considers seven different steel products monthly prices separately as the dependent variable from January 1997 to March 2005. As independent variables, industrial production index, iron ore, coal, steel scrap, industrial electricity price indexes, steelworkers wages in USD, the capacity index for steel production, currency exchange rates for major steel exporting countries, time trend, steel demand for China, antidumping and, safeguards are considered in the multivariate regression model. The lagged data of 3, 6 and, nine months are used in this study to show the delayed effects of the independent variables on the steel prices. The distinction of this research from previous ones is including China's growing demand in the model, which results in limiting producer countries' capability to export to the U.S. and EU as the major importers of steel. With consideration to %98 (R^2), the model looks appropriate for the designation of the U.S. steel market. The significant outcomes of this study are; first, the recovery of the steel industry in terms of prices had no statistical significance with safeguards as respected and Secondly, it is proved that the steel demand for china has a significant relationship with steel prices; therefore, after the retardation of six months.

The master thesis by Yuzefovych (2006) inspected the Ukrainian steel industry and compared it to the developed countries' steel industries. The author aims to find out the consequences of joining the *World Trade Organization (WTO)* in the steel industry. She used monthly observations from 1999 to 2005. The method of the research is the *Simultaneous Equation Model (SEM)*, which is used widely in econometrics when simultaneity is present. In this study, the price and quantity of steel production are two endogenous variables that depend on each other. Explanatory variables are used in the model are the quantity and capacity of the steel production, industrial production index of the EU, U.S., China, and Turkey, Gross National Product of the Ukrain (GNP), iron ore and coking coal prices. For obtaining results from the SEM model, *two and three-stage least square (2SLS and 3SLS)* estimations are used. The study proved that the Ukrainian steel industry had passed its transition stage, and there is a little risk of being hurt by joining WTO.

Following the studies on the U.S. steel industry as a primary importer of steel products, Blonigen, Liebman, & Wilson (2007) modeled the industry by econometric model. The research aims to find the ability of domestic steel producers to set a price above the marginal cost. To this aim, they used three equations in the SEM model as the quantity of demand, the quantity of import (supply) and, price. As explanatory factors index of industrial production, the real price of aluminum (as an alternative to steel), the exchange rate of exporter countries, other countries GDP, input prices (iron ore, metallurgical coal, oil) and, dummy variables to differentiate the period of trade policies are used. For annual steel prices data, 20 different steel products from 1980 to 2006 are used. For calculating the three equation system, the three-stage least square method (3SLS) is used. The results are suggested that trade policies made to protect the steel industry were statistically insignificant, except for the 1980's second half *Voluntary Restraint Agreement (VRA).*

In the paper published by Malanichev & Vorobyev (2011), they gave an effort to make a universal model for forecasting the global average annual steel prices based on the multivariate regression method. The forecast horizon was intermediate, which applied for the 2010-2012 period. The historical prices of the hot-rolled steel for four regions as the United States, Europe, China, and Russia from 1980 to 2009 were used as the dependent variable. For independent variables, Capacity Utilization, Raw Material Costs and, Time Trend is taken into the model. Capacity utilization is defined as the ratio of steel production divided by the steelmaking capacity of marginal producers around the world. Due to the equilibrium theory of demand and supply in the steel market, it is assumed that production (supply) is equal to consumption (demand), thus supply, demand and, steelmaking capacity explained by the dimensionless rate of capacity utilization. Raw material cost item is also determined by the weighted sum of iron ore and metallurgical coal usage per ton of steel. The authors claim that with the obtained model, for %7.5 growth in Capacity Utilization, the price of hot-rolled steel increases by 100 USD. Furthermore, increasing 1 USD in raw material costs results in an increase of 3 USD in hot-rolled steel prices. At the same time, the time trend presents a 5.2 USD decrease per each year due to the technological advancements in producing plants result in lower making costs. For the forecast of each independent variable in this study, a consensus forecast is prepared according to the global investment banks and specialized metallurgical agencies' reports for capacity and raw materials costs.

Recently with improvements in the computential power and expansion of new models, it has become possible to use sophisticated new models for economic indicators. Before these advancements, researchers mostly had been relied on conventional types of regression analysis to make forecast models. Some newer techniques, such as complex *ARIMA* based models, *M-SSA*. are used frequently with the help of software packages. Also, lately, the application of Machine-Learning Algorithms, especially *Artificial Neural Networks (ANN),* has made a tremendous milestone in forecasting economic indicators. In the following paragraphs, some papers on forecasting steel prices with current methods will be described.

Kapl & Müller (2010) has compared the *Auto-Regressive Integrated Moving Average (ARIMA)* with explanatory variables and a non-parametric spectral estimation model called *Multi-Channel Singular Spectrum Analysis (M-SSA)* for modeling and forecasting steel prices. For ARIMA with explanatory variables, lagged steel prices, lagged log of the coke prices, predictions of real GDP, lagged Dow-Jones index, and effectual exchange rates are used in the model. The M-SSA model is based on time series of hot-rolled coil prices, real GDP, index of the industrial production, the oil prices and, the Dow Jones stock index. It is concluded that while both methods have equivalent results regarding forecast error, the M-SSA method has larger amenability for generalization.

Chou (2013) worked on a model for long-term forecasting of global steel prices index through fuzzy time series, which was first introduced by Lotfi A. Zadeh in 1965. The author tried to make a forecast model for steel prices based on bulk shipping prices, Which are essential in the investment decision process for transportation companies.

Wu & Zhu (2012) attempted to predict steel prices for a week ahead through two univariate models. They utilized *Radial Basis Function (RBF)* Neural Networks and *Adaptive Sliding Window (ASW)* models using eight steel product prices from January 2011 to December 2011. For comparing two methods, Mean Absolute Errors (MAE) are used. The results proved that the ASW method is more suitable for forecasting steel market prices regarding forecast error.

Liu et al. (2014) used the *Back Propagation Neural Network (BPNN)* algorithm to forecast the steel prices index in China for the data from 2011 to 2013. The BPNN is a three-layer *Feed Forward Neural Network (FFNN)* that trains for errors by the Back Propagation algorithm. After correlation analysis was done for various factors, the iron ore price index, coke price index, and the average monthly trading volume of rebar steel are selected as inputs. For the output, the rebar steel price index is used. The article is concluded that the BPNN can forecast steel prices with excellent accuracy.

As a qualitative review study for the U.S. steel industry, Popescu et al. (2016) reviewed the effect of the steel imports on the U.S. steel industry. The study is pointed out some data about the crisis initiated by dishonest competition in the U.S. steel market as a result of the low-price steel products import.

Akman (2016) investigated the effect of the EUR/USD currency pair movements on the steel prices in Turkey as one of the largest steel producer countries. The study used the VAR model to determine the underlying relationship between pair currency relationship and steel prices.

As seen from the literature, there are limited researches that addressed forecasting in the steel industry, even though steel products are essential as physical and financial assets. One reason might be the overwhelming research enthusiasm about precious metals that can be beneficial in trades and result in the lesser notice for base metals. Another possible reason can be the unavailability of the data about the steel industry due to the strategic importance of the steel data for some countries.

The methodology which is used in most of the studies is econometric models. since econometric models comparing to data-driven models like the ANN and Fuzzy models can also reveal the underlying relationships among the variables besides the forecast process. Although, the ANN models might be able to forecast more accurately, therefore, due to black-box behavior, they unable to show the economic relationships which is the second most essential interest for econometricians and business forecasters.

III. METHODOLOGY

A. Definitions

Time Series and Stationarity

For describing the models that are used in this study, it is necessary to explain some fundamental definitions in time series analysis. According to George Box & Jenkins (1976), A collection of observations created sequentially in time order is called time series.

Time series can be stationary or non-stationary. In general, stationary time series are the ones that their pattern is independent of the observed time period. It means stationary time series should have a fixed mean and variance which do not vary with time (weak or wide-sense stationarity). There is another type of stationarity in time series which is called strict stationarity that requires covariance stability, besides mean and variance stability. However, this kind of stationarity is beyond the scope of the current study and not required in the models are used.

In another perspective, non-stationary time series is defined by random walks, drift, trend, and shifting variance. Defining time-series stationarity has a substantial role in econometric models.

Autocorrelation and Partial Autocorrelation Function

The *Autocorrelation Function (ACF)* is similar to correlation definition, which measures a linear relationship between two variables(series), while ACF assesses linear relationship within the variable with its time lags (Rob J Hyndman and Athanasopoulos 2018). The ACF is represented by equation 1.

$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \qquad \textbf{(3.1)}$$

Where $\boldsymbol{T}$ is the time period of the series, and $\boldsymbol{k}$ is the number of the lags.

The Partial Autocorrelation Function (PACF) is used with *ACF* in an association to reveal patterns in the data. The PACF results in autocorrelation between the current and *k*th lag while it controls the effects of other lags (Yaffee 1999). Both ACF and PACF play an essential role in identifying the characteristics of a time series. The patterns of ACF help to discover trends and seasonality in the time series.

Tests for Non-Stationarity

While with the contribution of the ACF and PACF, we can detect non-stationarity graphically; therefore, some tests are available to provide statistical evidence on the existence of the non-stationarity. There are several tests, including *KPSS, Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF) and, Philips-Perron.* Despite its weaknesses, the most reputable non-stationarity test in literature is the ADF test, which is an extended version of the DF test.

The ADF test, which is introduced by Said & Dickey (1984), is the extension of the *Dickey-Fuller (DF) test* by Dickey & Fuller (1979) while allows detecting higher unit root order. The unit root is the characteristic of time series, which causes random walk (non-stationarity). The null hypothesis for the ADF test is that there is a unit root in the time series. The alternate hypothesis has three versions: 1) no unit root (random walk model), 2) no random walk with drift, 3) trend stationary. It means that if the test statistic is high enough regarding the significance level to reject the null hypothesis, then we can conclude that the time series is stationary. The test is using the principles of the Box-Jenkins Autoregression model.

Time Series Transformations

Most of the real-world financial time series represent non-stationarity, which in most cases they have to be converted to stationary series before applying in econometric models.

Weak stationary requires stability both in the mean and variance of the time series. Due to volatility and fluctuations resulted from seasonality and interventions in the financial time series, some transformations may be applied to stabilize the variance, such as natural logarithm, logarithm, square root, square, and Box-Cox transformations. Thus these transformations may render a time series into a series with finite variance (variance stability). In the literature, using the natural log for stabilizing the variance of financial series is a common practice.

For stabilizing the mean, the type of the trend(s) must be identified before try to render the time series into stationary. Since for stabilizing the mean, the trend may be modeled or eliminated. The determination of the trend can be done with the ADF test, considering the different variations of the test.

The deterministic trend is a result of the deterministic model, which gives the same result with given inputs in every implementation. Hence for de-trend, the deterministic trend first or higher-order regression equations may be used to model the deterministic trends. On the other hand, stochastic trends are the result of some stochastic process and cannot be modeled. To convert the time series into stationary series with the stochastic trend, first or higher-order differencing will be required. In differencing, each observation is subtracted from its own lag.

Generally, for the real-world settings, concerning the existence of both trends and fluctuations, a combination of transformations and de-trend or differencing may be used to render the time series into stationary.

B. Causality

The causality or cause-and-effect in statistics is referred to as the relationship whenever a variable's lags affect another variable. The utilization of the causality in forecasting is based on the idea that cause cannot come after effect. Thus the determination of cause helps to improve the forecast in the target variable.

The concept of causality in economics initially introduced by Granger (1969) describes the effect of variable X's lags on variable Y, and in contrast, the effect of variable Y's lags on variable X. The Granger causality test procedure consists of two autoregressive equations that each equation tests for causality, based on other variables. The mathematical representation of the Granger causality is shown by equation (2).

$$\begin{cases} Y_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + u_{1t} \\ X_t = \sum_{i=1}^{n} \lambda_i Y_{t-i} + \sum_{j=1}^{n} \sigma_j X_{t-j} + u_{2t} \end{cases} \tag{3.2}$$

While α and σ are the coefficients for each variable's own lags, β and λ are the coefficients for the variables are assessed for the Granger causality. When β and

λ coefficients are statistically different from zero, we can conclude that each variable Granger causes other variables and vice-versa. Therefore, the null hypothesis for the Granger causality is no Granger causality, which means that the rejection of the null hypothesis proves the causality between the variables in each of the directions. Also, two-way causality (feedback) is possible between variables.

Due to the utilization of autoregressive equations, the assumption of the Granger test for variables is to be stationary. Hence in the case of non-stationarity, variables must be converted to the stationary process by differencing.

C. Vector Autoregression Model

The VAR model is an extension of the univariate ARIMA model that has the capability of multivariate analysis. The VAR model introduced by Sims (1980) is an attempt to solve the problems about the determination of the exogeneity for the variables in the conventional statistical model. Therefore, in the VAR model, all the variables are treated as endogenous variables, and there is an equation for each of the variables as an endogenous (dependent) variable. The model description for VAR is adopted from Enders (2014).

For simplicity, a bi-variate first-order VAR model is explained in the methodology part, which can be generalized for multiple variables as well.

We assume that Y_t is being affected by the current and previous values of the $X_{t,}$ and in contrast, X_t is being affected by the current and past values of the Y_t as well. the formulation of the bi-variate model is shown in equations 3.3 and 3.4.

$$Yt = b_{10} - b_{12}X_t + \alpha_{11}Y_{t-1} + \alpha_{12}X_{t-1} + \varepsilon_{yt} \qquad \textbf{(3.3)}$$

$$Xt = b_{20} - b_{21}Y_t + \alpha_{21}Y_{t-1} + \alpha_{22}X_{t-1} + \varepsilon_{xt} \qquad \textbf{(3.4)}$$

Where b_{10} and b_{20} are constant term for equations, Y_t and X_t are stationary series and ε_{yt} and ε_{xt} are white-noise residuals, which means there are no patterns that exist in the residuals after modeled by the equations. Equations 3.3 and 3.4 cannot be estimated directly through *Ordinary Least Square (OLS)*. Due to the inclusion of the current value of X_t in the Y_t's equation and vice-e-versa, which makes the residuals of the two equations correlated. Consequently, the correlation of residual terms results in the system's bias and violates the assumption of the independent residuals for the OLS system.

For this reason, a transformation of the system through matrix algebra is needed to solve this problem. The matrix representation of the above two-equation system is demonstrated in equation 3.5.

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix} \begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{bmatrix} \tag{3.5}$$

Or we can write as equation 3.6.

$$BZ_t = \Gamma_0 + \Gamma_1 Z_{t-1} + \varepsilon_t \tag{3.6}$$

Where:

$B = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}$, $Z_t = \begin{bmatrix} Y_t \\ X_t \end{bmatrix}$, $\Gamma_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}$, $\Gamma_1 = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}$ and, $\varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{bmatrix}$

By pre-multiplication of both sides of the equation 3.6 to B^{-1} matrix, the reduced form of the VAR model is obtained in equation 3.7.

$$Z_t = \mathrm{A}_0 + \mathrm{A}_1 Z_{t-1} + e_t \tag{3.7}$$

Where $\mathrm{A}_0 = B^{-1}\Gamma_0$, $\mathrm{A}_1 = B^{-1}\Gamma_1$, and $\mathrm{e}_t = B^{-1}\varepsilon_t$.

With assigning a_{i0} as the element of the vector A_0, a_{ij} as the element of the matrix A_1 with (i) for rows and (j) for columns and, e_{it} as the element of the vector e_t the VAR model can be formed as equations 3.8 and 3.9.

$$Yt = a_{10} + a_{11}Y_{t-1} + a_{12}Z_{t-1} + e_{1t} \tag{3.8}$$

$$Zt = a_{20} + a_{21}Y_{t-1} + a_{22}Z_{t-1} + e_{2t} \tag{3.9}$$

While equations 3.3 and 3.4 are called the structural VAR and contain current values of the variables, equations 3.8 and 3.9 are called reduced-form or standard form VAR.

In order to form a VAR model with multiple variables, the same methodology is used as well. The matrix representation of the VAR model for multiple variables is reported in equation 3.10.

$$\begin{bmatrix} Z_{1t} \\ Z_{2t} \\ \cdot \\ Z_{nt} \end{bmatrix} = \begin{bmatrix} A_{10} \\ A_{20} \\ \cdot \\ A_{n0} \end{bmatrix} + \begin{bmatrix} A_{11}(B) & A_{12}(B) & \cdot & A_{1n}(B) \\ A_{21}(B) & A_{22}(B) & : & A_{2n}(B) \\ \cdot & \cdot & & \cdot \\ A_{n1}(B) & A_{n2}(B) & \cdot & A_{nn}(B) \end{bmatrix} \begin{bmatrix} Z_{1t-1} \\ Z_{2t-1} \\ \cdot \\ Z_{nt-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ \cdot \\ e_{nt} \end{bmatrix} \tag{3.10}$$

To summarize and simplify algebraic lag operators in the time series, usually, the sign is known as *Backshift Notation* ***(B)*** is used.

Some matrix operations and algebraic simplifications are used to form the final reduced-form VAR (P), which can be shown as equation 3.11.

$$Z_t = \delta + \sum_{i=1}^{P} \Gamma_i Z_{t-i} + e_t \tag{3.11}$$

Where Z_t is (N × 1) vector of endogenous variables, δ is (N × 1) constant term vector, Γ_i is (N × N) matrix of coefficients, and e_t is (N × 1) vector of the white noise residuals.

The estimation for the VAR model is OLS, which means each equation in the VAR system can be estimated using OLS. Residuals in OLS estimation are assumed to be not autocorrelated, in addition to the constant variance.

Selection of optimal lag length (P) in the VAR process is made with consideration to information criteria like *Likelihood Ratio (LR), Akaike's Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz information criterion (SIC),* or *Bayesian Information Criterion (BIC),* and, *Hannan-Quinn Information Criterion (HQ).* However, Lütkepohl (2005) suggested that selecting optimal lag length is not a crucial point when the primary goal of the modeling is just forecasting. For the model fit, Gredenhoff & Karlsson (1999) showed that AIC performs more favorable results rather than rivals.

The AIC is being used in the current study for selecting the optimal lag length, and the basic formula is demonstrated as equation 3.12.

$$AIC = -2(log - likelihood) + 2K \tag{3.12}$$

The log-likelihood is a natural logarithm transformation of the likelihood function, which is used to assess the integrity of the model to the data. K is the number of model parameters, including the intercept.

D. Cointegration and Vector Error Correction Model

Initially, for describing the cointegration, the integration order *I(d)* and economic equilibrium have to be explained.

In order to transform the nonstationary time series with unit root to stationary series, the differencing is needed. The number of differences is defined by *I(d),* which d is the order of integration. In economics, the Equibilirium or Market-clearing is a situation in which economic forces (e.g., price, demand, supply), in the lack of external interventions, remain in balance.

Firstly, Engle & Granger (1987) formulized the underlying linear relationship among integrated variables after studies by Yule (1926) and Granger & Newbold (1974), which assessed the spurious correlation between non-stationary variables. Regarding Granger (1981), the cointegration among two variables is a proportionate movement onwards the long-run fluctuations (equilibrium), excluding the short-term dynamics (lags of the variables). Generally, it is possible to have a cointegration in less order than *d*, between the variables with integration order of *d*.

In the economy, most of the financial data are integrated of order 1, which means that cointegration relation among the variables would be a stationary process in case of existence. The mathematical expression of the cointegration process, as explained in Granger (1981) and Engle & Granger (1987), is shown in equations 3.13 and 3.14.

Assume that all the variables of interest collected in a vector y_t as:

$$y_t = (y_{1t}, \dots, y_{kt})' \qquad \textbf{(3.13)}$$

And the long-run equilibrium relationship is defined by:

$$\beta' y_t = \beta_1 y_{1t} + \cdots + \beta_K y_{Kt},\ \beta = (\beta_1, \dots, \beta_K)',\ \text{and},\ \beta' y_t = z_t \qquad \textbf{(3.14)}$$

Where z_t is assumed as a stochastic variable that indicates the departure from the long-run equilibrium. If all components of y_t are integrated of order (d), and a linear combination exists as: $(\beta' y_t = z_t)$ with $\beta = (\beta_1, \dots, \beta_K)' \neq 0$, then it can be possible that z_t is the cointegration relationship between variables with the order of integration I (d-b). Also, the vector β is named the cointegration vector, which is not exclusive, since it can be possible to have multiple linearly independent cointegrated vectors.

There are two approaches to test the cointegration among variables. First, the Engle & Granger (1987) test procedure, which can only demonstrate single cointegration between two variables with a single equation model, as another option, the Johansen test procedure was introduced by Johansen (1991) and Johansen & Juselius (1990), which can be more practical since it can be used for several variables and unveils more than one combination of the cointegration vectors among the variables.

The Johansen procedure uses two types of tests as *Trace*, and *Maximum Eigenvalue* tests, which the former is from the linear algebra, and the ladder is a scalar. The null hypothesis for both tests is in favor of no cointegration among variables. The difference between these tests arises in the alternate hypothesis. The Trace test alternate hypothesis is that there is at least one cointegration combination. The Maximum Eigenvalue test alternate hypothesis is that there is a cointegration combination with the addition of one (K_0+1).

According to the literature, the Trace test in Johansen Procedure performs better than the Maximum Eigenvalue test, mainly when it is suspected to have more than one cointegration combinations (Cheung and Lai 2009; Lütkepohl, Saikkonen, and Trenkler 2001).

The assumption for the *Autoregressive (AR)* model, which also the VAR model is based on, is that variables have to be stationary. For the VAR model to be stationary, the roots (coefficients) should be outside the unit root circle of the equations embedded in the VAR system. The majority of the economic variables are non-stationary variables which transforming them into stationary process result in the loss of some critical features of the variable like trends and long-run relationships. Thus, performing the VAR model with differenced data expels the plausible long-run relationship among the data.

In the literature, it is discussed that the VAR system can handle the non-stationarity by running on level variables (LVAR), which in this case, it gives consistent parameter estimation without eliminating the long-run dynamics in the cointegrated variables (Phillips and Durlauf 1986; Sims, Stock, and Watson 1990; West 1988).

For modeling cointegrated variables considering both short-run and long-run dynamics, the Error Correction Model (ECM) was introduced by Engle & Granger (1987), which is a particular case of the VAR model. This is a two-stage model with a single equation along with the endogenous variable and multiple exogenous variables, which allows for one set of cointegration to be modeled. Another approach is Johansen's Vector Error Correction Model (VECM) by Johansen (1991), which uses the VAR model to formulate the numerous cointegrations (long-run dynamics) along with the short-run dynamics as well.

The two variables system is used to explain more straightforwardly for the ECM model in equations 3.15 to 3.17. Assume that the long-run relationship (equilibrium) between two variables is:

$$y_{1t} = \beta_1 y_{2t} \tag{3.15}$$

Where the alterations in y_{1t} , based on departures from the equilibrium in the previous period (t-1). We use the differenced variables, which are represented by the Δ sign.

$$\Delta y_{1t} = A_1(y_{1,t-1} - \beta_1 y_{2,t-1}) + u_{1t} \tag{3.16}$$

For y_{2t} a similar equation can be formed:

$$\Delta y_{2t} = A_2(y_{1,t-1} - \beta_1 y_{2,t-1}) + u_{2t} \tag{3.17}$$

In an extensive form, the Δy_{it} can depend on previous lags of its own and other variables in addition to the long-run dynamics.

$$\Delta y_{1t} = A_1(y_{1,t-1} - \beta_1 y_{2,t-1}) + \gamma_{11,1}\Delta y_{1,t-1} + \gamma_{12,1}\Delta y_{2,t-1} + u_{1t}$$

$$\Delta y_{2t} = A_2(y_{1,t-1} - \beta_1 y_{2,t-1}) + \gamma_{21,1}\Delta y_{1,t-1} + \gamma_{22,1}\Delta y_{2,t-1} + u_{2t} \tag{3.18}$$

Also, it is possible to include the further lags of the variables.

To write the 3.18 equations as matrix representation, they can be written as:

$$\Delta y_t = A\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + u_t \qquad \textbf{(3.19)}$$

Where:

$y_t = (y_{1t}, y_{2t})'$, $u_t = (u_{1t}, u_{2t})'$, $A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix}$, $\beta' = (1, -\beta_1)$, and

$$\Gamma_1 = \begin{bmatrix} \gamma_{11,1} & \gamma_{12,1} \\ \gamma_{21,1} & \gamma_{22,1} \end{bmatrix}$$

The VEC model with intercept term can be written with the help of some algebraic modifications and simplifications by using matrix notation, as:

$$\Delta Z_t = \delta + \sum_{i=1}^{P-1} \Gamma_i \Delta Z_{t-i} + \Pi_{y_{t-1}} + e_t \qquad \textbf{(3.20)}$$

Where Z_t is (N × 1) vector of endogenous variables, δ is (N × 1) constant term vector, Γ_i is (N × N) matrix of coefficients for short-run dynamics, Π is the matrix of coefficients for Error Correction Term (ECT), and e_t is (N × 1) vector of the white noise residuals. The ECT demonstrates the speed of correction towards the long-run dynamics due to the interventions. While the Negative ECT sign shows the convergence of the shock along with the equilibrium, the positive sign demonstrates explosive or divergence behavior. It is important to notice that the lag length criteria which is determined in VAR (p) model is also applicable to VEC model with (p-1) since lagged differences in VEC model represent to VAR (p) (Lütkepohl 2005a).

Unlike the VAR model on levels (LVAR), the VEC model differentiates the short-run dynamics from the long-run dynamics. The VEC model uses differenced variables to investigate the short-run, and it includes the cointegration equation to the model to assess the long-run dynamics.

According to Shoesmith (1995), some problems occur in the case of multiple cointegrations presence [1]. Mostly, it becomes more problematic when these cointegration relationships are not compatible with economic theories. However, despite these problems, using any combination of cointegration relationships may improve the forecast accuracy as well (Shoesmith 1995a).

[1] See (Shoesmith 1992, 1995a) for more details

E. Impulse Response Function

For investigating the interactions among the variables, in addition to the Granger causality analysis, the Impulse Response Function (IRF), which is generalized by Pesaran and Shin (1998) is used as well. The IRF shows the reaction of the variable of the interest to exogenous shocks or interventions, which usually are called shocks in the economics literature. Often the IRFs are modeled in the context of the VAR and VEC models, where regardless of the endogenous description of these systems, impulses are treated as an exogenous variable to the response in the variable of the interest.

Usually, the IRF is formulated as the Vector Moving Average (VMA) representation of the VAR model as equation 3.21.

$$y_t = \delta + \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i} \tag{3.21}$$

Where the components of the ε_t are independent, which are representative of the MA process. The δ is the intercept term. The unit of a shock in each component is one standard deviation.

F. Forecast Error Variance Decomposition

The Forecast Error Variance Decomposition (FEVD) is another tool to investigate the interconnections among multiple variables in the VAR or VEC models. The FEVD indicates the proportionated movements through the time, based on the variable's own shocks against other variables shocks (Lütkepohl 2005b). In a VAR model, the FEVD shows the proportional contribution of each variable to forecasting the variable of interest. For estimation of FEVD, the Mean Squared Error (MSE), as a forecast error measurement along with MA representation of the process, is used. The equation to estimate the FEVD is illustrated as 3.20.

$$\omega_{jk,h} = \sum_{i=0}^{h-1} (e'_j \Theta_i e_k)^2 \,/ MSE\left[y_{j,t}(h)\right] \tag{3.22}$$

The $\omega_{jk,h}$ is the proportion of the h-step FEVD of the variable j comprised of interventions or shocks in variable k.

G. Forecast Accuracy Measures

The forecast accuracy measures are obtained using forecast errors with different methods. Basically, forecast error is a difference between the actual value and forecasted value of the variable at the given time. The forecast errors can be aggregated into the measures which show the accuracy of the measures. The forecast accuracy measures have some variations where some of them are on the level of the variables, and some are on the percentage of changes. However, not all of the forecast accuracy measures are useful in comparing different models, forecast results. While Many studies looked into the efficiency of the different forecast accuracy measures, few of them can suggest the superiority and efficiency of one over others. Studies show that the selection of the suitable measure highly depends on the variable types and models which are used to analyze the variables.

The most used measures to compare two model's forecast accuracy are *Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE)* regarding the literature. Chai & Draxler (2014) showed that the RMSE could outperform the MAE when the error term of the model are normally distributed. furthermore, Armstrong & Collopy (1992) declare the improperness of using RMSE for models with different methodologies.

The MAPE is often used as an efficient and practical comparison measure for forecast accuracy owing to its naïve interpretation as a unit-less measure in percentage. It can be used for the data with a significant difference from zero and positive values confidently (Hyndman and Koehler 2006).

The mathematical representation for RMSE and MAPE are showed in equations 3.21 and 3.22.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{3.23}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{3.24}$$

Where the *(n)* is the number of observation, the y_t and $\hat{y}_t$ are the actual value and forecasted value of the variable, respectively.

IV. EMPIRICAL RESULTS

A. Data Description

The data being used in this study are monthly data from January 2009 to June 2020 for 138 months. All the variables are selected, respecting the literature which investigates the United States steel industry. All the variables seasonally adjusted to use with VAR and VEC models, since these models are not compatible with seasonal data. For simplicity reason, all the variables are converted to index form as of January 2009 = 100.

The U.S. Bureau of Labor Statistics (BLS) introduced the Producer Price Index (PPI) measure as "the average change over time in the selling prices received by domestic producers for their output." As a result, the PPI is a suitable indicator of commodity prices. For investigating the steel prices for the United States, the PPI of Steel Mill Products **(ST)** (U.S. Bureau of Labor Statistics 2020c) is used. The steel mill products refer to the whole steel products with different shapes that are being manufactured from melted steel. The other explanatory variables that are used to predict the steel prices are selected carefully from the dedicated literature about the United States steel industry since the 1950s.

As explanatory variables, two class of variables are utilized in this study. The raw materials that are used in the steel making process as:

a) The PPI for Iron and Steel Scrap **(SC)** (U.S. Bureau of Labor Statistics 2020b).
b) The Global Price of 62%-Fe Iron Ore **(IO)** (US$/ton) (International Monetary Fund 2020b).
c) The global spot prices of Coal for Australia as the largest coal exporter in the world **(CO)** (US$/ton) (International Monetary Fund 2020a).

On the other hand, there are some economic indicators which represent the steel industry's vulnerability and demand as:

d) Import Price Index (End User) for Iron and Steel Mill Products **(IM)** (U.S. Bureau of Labor Statistics 2020a).

e) The Value of Manufacturers' New Orders for Iron and Steel Mills **(NO)** (M$) (U.S. Census Bureau 2020).

The **(IM)** renders the prices of imported finished and semi-finished steel and iron products to the United States from the exporter countries. This variable is one of the most critical variables to the United States steel, given that several studies investigate it as a cause of injury to the domestic producers of the steel (Blecker 1989; Blonigen et al. 2007; Grossman 1986; Liebman 2006; Mancke 1968).

The **(NO)** is included in the class of indicators called *Factory Orders*, which offered by the United States Census Bureau as an indication of the value of the goods from the factories in the US dollar. The **(NO)** reflects the manufactures' plans to buy goods with immediate or future delivery. In another way, it represents the increasing or decreasing demand for the manufacturing factories for iron and steel products. The variables' descriptive statistics are reported in Table 1.

Table 1 Descriptive Statistics

	ST	**SC**	**IO**	**CO**	**IM**	**NO**
Mean	107.8069	153.5401	138.0583	104.9097	94.32692	180.7735
Median	108.3054	159.7517	124.0722	103.5088	95.57693	186.6245
Maximum	126.0067	217.7066	258.1469	164.7858	117.6442	238.0455
Minimum	85.57047	75.69422	56.38274	62.44489	66.73077	78.87789
Std. Dev.	10.03676	35.99589	52.35592	25.65674	11.28606	30.55172
Observations	138	138	138	138	138	138

Notes: All of the variable indexed as Jan. 2009 = 100.

Also, the graphs for the indices of the variables are printed in Figure 1.

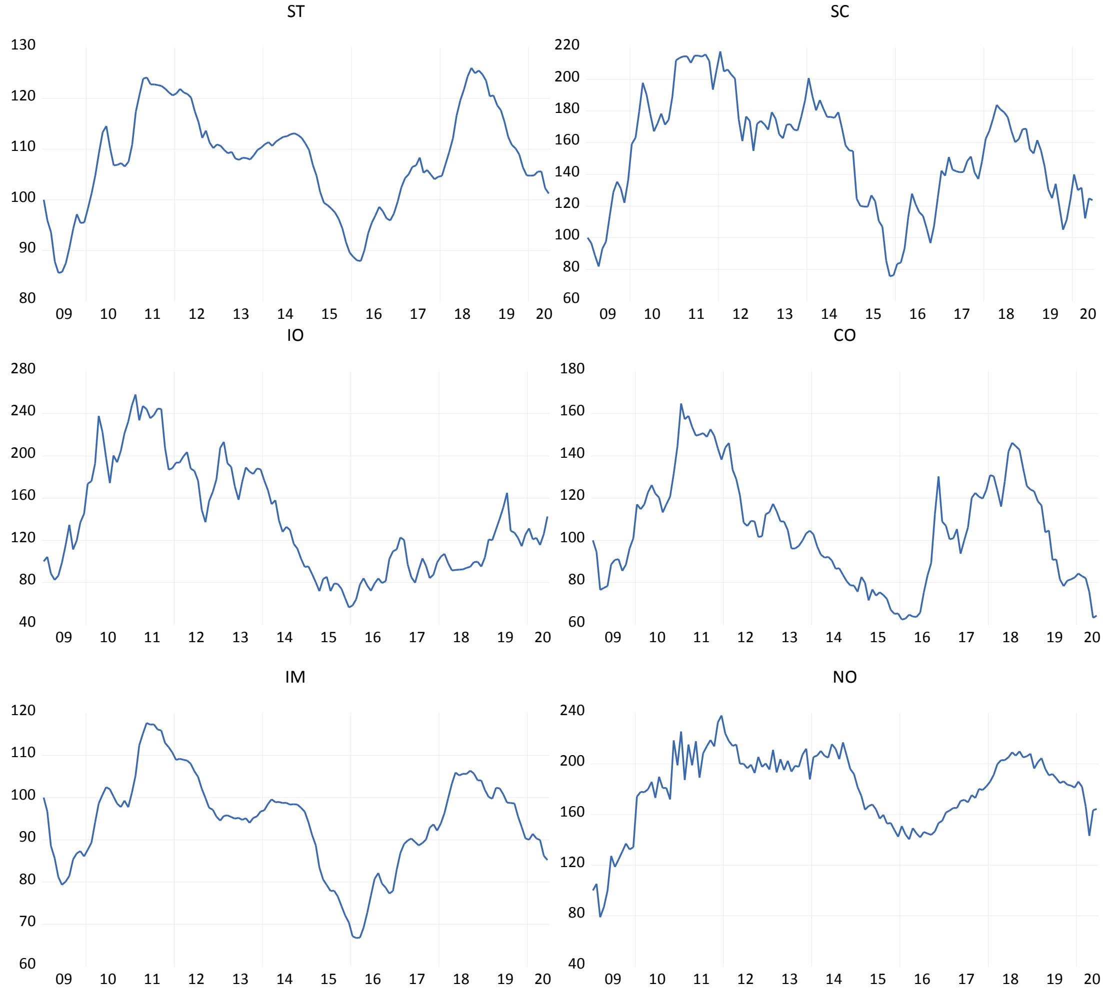

Figure 1: Variable Indices (Jan. 2009 – Jun. 2020)

As seen from the graphs, all the variables almost follow the same patterns. The peak point in variables is around 2011, which implies the global commodity boom following the recovery from the 2008 great recession due to growing demand from the emerging markets and, besides, the deficit of the supply. In contrast, the decline around 2015 and 2016 is a sign of industrial mini-recession, which was occurred as a result of a slowdown in business investments. The decline was mostly in the energy and manufacturing sectors of the economy, which was arisen from the downshift of the emerging markets. Moreover, from the beginning of 2019, as a consequence of the intense trade war between the U.S. and China, followed by the spread of the novel Covid-19 virus, which has paralyzed the global economy, commodity prices started to fall sharply.

As observed from the graphs, the variables for this study, similar to the most financial series, are volatile data, which causes instability in the variance over time. The main reason for significant fluctuations in the data lies within the existence of extreme values (outliers) around 2011 and 2015 as the peak and bottom points. The (Ln) transformations are applied to all variables to decrease the negative effect of the outliers in the models and stabilize the variance. The data from January 2009 to December 2018 are used in the modeling process below. The data from January 2019 to June 2020 are used to validate the forecast against actual values.

B. Preliminary Analysis

To form the VAR and VEC models, some assumptions have to be fulfilled before starting to model with selected variables. Since the VAR and, consequently, the VEC models are the expansion of the Box-Jenkins ARIMA model, check for the stationarity state of the variables is a crucial step toward the modeling process.

Regarding the Sims (1980) VAR model specification, all the variables that are included in the system must be the first order of the integration as I (1), which means they need to be differenced once to render into the stationary process [2]. It is pointed out that most of the economic and financial variables have low orders of integration [3].

The variation of the ADF test, which is used in this study, is performed without the inclusion of the intercept and trend in the ADF equation. The results of the ADF test on levels and after first differencing of the variables with corresponding t-statistics and p-values are represented in table 2.

Table 2 ADF test results

Variables	t-stat.	Prob.	Δ Variables	t-stat	Prob.
LnST	0.178783	0.7366	Δ LnST	-5.518522	0.0000
LnSC	0.097150	0.7119	Δ LnSC	-8.819061	0.0000
LnIO	0.314639	0.7752	Δ LnIO	-8.868412	0.0000
LnCO	-0.449434	0.5185	Δ LnCO	-9.035877	0.0000
LnIM	-0.203410	0.6113	Δ LnIM	-5.395454	0.0000
LnNO	0.528214	0.8288	Δ LnNO	-4.587397	0.0000

Notes: Δ = first difference

As observed from the results of the ADF test, for all first differenced variables, the null hypothesis can be rejected. Hence, all the variables are proved to be integrated of order one, I (1), which means can be modeled with VAR and VEC model, conclusively.

[2] For models with different order of integration see (Pesaran, M. H., Shin 1999)
[3] For VAR models with higher orders of the integration see (Toda and Yamamoto 1995)

The next step after approval of the variables regarding stationarity is to select the variables that are efficient in steel price prediction. The conventional *Pearson Correlation* is used frequently to define the relationship among the variables, and therefore in the case of forecasting, the more important relationship is the causation, which shows the effect of one variable on another variable and thus has a predictability power for the variable of the interest. The strong correlation does not mean definite causation between variables. For this reason, relying on correlation analysis solely results in misleading relationships in forecasting. In this study, both analyses are employed in the variable selection process. The correlation coefficients between variables are reported in Table 3.

Table 3 The Pearson Correlation Results

Variables:	LnST	LnSC	LnIO	LnCO	LnIM	LnNO
LnST	1.000000					
LnSC	*0.815420	1.000000				
LnIO	*0.552596	*0.764679	1.000000			
LnCO	*0.688655	*0.755427	*0.616875	1.000000		
LnIM	*0.909525	*0.827220	*0.690730	*0.757619	1.000000	
LnNO	*0.824304	*0.798895	*0.528376	*0.542507	*0.664515	1.000000

Notes: * 5% significance level

The significant correlations between the variables are observed, which is essential to the variable selection procedure, but after further analysis of the Granger causation relationship, where is demonstrated in Table 4.

Table 4 Granger Causality test for LnST variable

Null Hypothesis:	Lag 2 Prob.	Lag 3 Prob.	**Lag 4 Prob.**
ΔLnSC on ΔLnST	$2. \times 10^{-11}$	$5. \times 10^{-10}$	**$2. \times 10^{-9}$**
ΔLnST on ΔLnSC	0.2526	0.0958	**0.625**
ΔLnIO on ΔLnST	0.0005	0.0025	**0.0045**
ΔLnST on ΔLnIO	0.9516	0.6596	**0.8141**
ΔLnCO on ΔLnST	0.0027	0.0156	**0.0179**
ΔLnST on ΔLnCO	0.9310	0.5856	**0.3308**
ΔLnIM on ΔLnST	$3. \times 10^{-5}$	0.0023	**0.0133**
ΔLnST on ΔLnIM	$2. \times 10^{-7}$	$7. \times 10^{-6}$	**0.0001**
ΔLnNO on ΔLnST	$4. \times 10^{-5}$	0.0002	**$6. \times 10^{-7}$**
ΔLnST on ΔLnNO	0.2526	0.2556	**0.0727**

Notes: LnSC on LnST: that LnSC does not Granger Cause LnST

In the Granger causality analyses in Table 4, only the causation relationships of all variables with LnST are addressed, since only the LnST is the variable of interest in this study. All the variables except LnIM, have one-way Granger causality with LnST, which it means that LnSC, LnIO, LnCO, and LnNO have a causal relationship on LnST and in return, LnST does not cause an effect in these variables. Therefore, for LnIM, the causality is a two-way relationship, which implies that the causal relationship is running down from LnIM to LnST and from LnST to LnIM. Regardless of the two-way causality of the LnIM variable with the Target variable LnST, due to all variables causal relationship with LnST, it is approved that all nominated variables have predictability power on LnST and are suitable to make forecast models.

C. Suggested models

To start the modeling process with the VAR system, the first step is to define optimal lag length for the unrestricted VAR model, which is essential to establish the best VAR and, consequently, VEC models. The second step is to discover possible cointegration relationship(s), which is necessary to decide on modeling the VAR system with variables on levels or differences and then, to form the VEC model.

The initial step is to determine the maximum lag length for the model is to define the optimal lag length for the VAR model. As reviewed by the literature, the maximum time delay for explanatory variables to take effect in the steel industry is not further than 6 months. Thus, the maximum lag length for the model is set to 6 months. The ultimate stage of defining optimal lag length is to minimize the information criteria regarding the unrestricted VAR model (the model without any exogenous variables and constraints on coefficients). In this study, the AIC is used for this purpose due to superior performance in fitting the data to the model (Gredenhoff and Karlsson 1999). The E-Views software package is used to minimize the AIC, and results are showed in Table 5 as well.

Table 5 Optimal Lag Length Selection Criteria

Lags:	LR	FPE	AIC	SC	HQ
0	NA	5.91e-13	-11.12912	-10.98511	-11.07068
1	1292.605	6.31e-18	-22.57797	-21.56990	-22.16885
2	157.2414	2.51e-18*	-23.50324	-21.63110*	-22.74344*
3	58.42266	2.59e-18	-23.48663	-20.75043	-22.37616
4	60.10920*	2.54e-18	-23.53044*	-19.93018	-22.06929
5	35.19524	3.26e-18	-23.32290	-18.85857	-21.51108
6	38.00267	3.98e-18	-23.18486	-17.85647	-21.02237

Notes: * Indicates lag length selection by the criterion

As seen from Table 5, the lag order of the (4) with the AIC value of (-23.53044) is the lowest among the maximum lag of (6) months. Hence, the lag length of (4) is the optimal length for the VAR model.

In this study, the Johansen test is used to find possible cointegration combinations between the variables. As stated in the methodology section, the *Trace* test approach is utilized when more than one cointegration combination is suspected. The variables are used here may have multiple long-run relationships, Recalling the literature. While the optimal lag length for the unrestricted VAR model is defined as order (4), for testing cointegration, the lag length is reduced by one due to further application of the cointegration relationships in the VEC model that also uses reduced lag length by one. The Johansen Trace test approach results considering the existence of the intercept term and variables without trend in equations along with p-values are demonstrated in Table 6.

Table 6 Johansen Cointegration test Results for lag (3)

No. of Cointegrations	Trace Stat.	Prob.
None*	139.9078	0.0000
At most 1*	76.62493	0.0129
At most 2	43.70409	0.1163
At most 3	24.75459	0.1704
At most 4	8.470328	0.4166
At most 5	0.292014	0.5889

Notes:* = 5% significant.

Due to the rejection of the null hypothesis for none and at most one cointegration and to be unable to reject the null for at most 2 cointegration, it is appeared to be two cointegration combination between the variables. On account of the fact that there is two cointegration combination among variables, two models can be formed to exhibit both short-run and long-run dynamics of the data considering the literature. The LVAR model means forming the VAR system without differencing to avoid elimination of the long-run relationship and the VEC model, which adequately reflects both short-run and long-run dynamics using cointegration equations.

Usually, in the VAR systems, due to the use of a lagged form of the variables, the assumption of the independence between the variables is violated, which in return results in insignificant coefficients for some lags. This situation is called *multicollinearity*. When the VAR and VEC models are used to the interpretation of the economic relations, the multicollinearity can become problematic due to unrealistic and misleading coefficients. However, when the purpose of modeling is pure forecasting, the majority of studies suggest that multicollinearity is not a problem as long as the proposed model can forecast correctly (Anderson, Burnham, and Thompson 2000; Armstrong 2007; Kostenko and Hyndman 2008). As a result, the current study uses the full form of the models without excluding the insignificance coefficients and relating variables. To estimate the LVAR, model the lag length, which was obtained through the optimal lag length selection process, is used. The LVAR (4) model estimation and corresponding statistics are represented in Table 7.

In the table below, the first row shows the variable on the left side of the equation, and the first column represents variable lags that interact as the right side of the equation related to the specific variable, which is shown in the first row. The (C) is the intercept for each equation.

Table 7 LVAR (4) Estimation Results

Coefficients Estimation and p-values:						
Variables:	LnST	LnSC	LnIO	LnCO	LnIM	LnNO
LnST(-1)	0.983591*	-1.602512*	-0.665033	0.117094	0.003852	0.186819
LnST(-2)	-0.158653	1.056820*	1.056715	-0.682954	-0.136700	-1.021630
LnST(-3)	0.066424	0.644183	0.190641	0.174987	0.077488	0.601411
LnST(-4)	-0.187758	-0.937055	-0.829931	-0.030294	-0.069144	-0.443612
LnSC(-1)	0.079307*	0.961473*	0.164673	0.124336	0.075099*	0.209325*
LnSC(-2)	-0.067974*	-0.344265	-0.001052	-0.106990	0.049136	-0.102126
LnSC(-3)	-0.032195	-0.000135	-0.172711	0.240878	-0.039744	0.124086
LnSC(-4)	-0.010405	-0.216995	-0.093988	-0.168179	-0.070586*	-0.047241
LnIO(-1)	-0.010930	0.165067*	1.060782*	0.078273	0.014496	-0.008655
LnIO(-2)	0.018737	-0.154135	-0.474646*	-0.104045	-0.010583	-0.061512
LnIO(-3)	-0.026800	-0.014551	0.309969*	-0.032730	0.005589	0.182993*
LnIO(-4)	0.008963	0.070397	0.122185	0.027857	-0.013724	-0.146513*
LnCO(-1)	0.039115*	0.060836	0.416590*	1.150723*	-0.008540	0.057491
LnCO(-2)	-0.031888	0.116877	-0.391966	-0.329418*	0.044305	0.083127
LnCO(-3)	0.014407	-0.175398	0.314810	0.267880	0.037756	-0.084595
LnCO(-4)	-0.007718	0.072146	-0.214316	-0.137053	-0.042297	0.066332
LnIM(-1)	0.250468*	1.405870*	-0.550612	-1.115361	0.991761*	-0.720864
LnIM(-2)	-0.123241	-1.332900	0.250704	1.722924*	0.060799	0.642155
LnIM(-3)	-0.065338	0.651002	-0.459637	0.390834	-0.103426	0.189188
LnIM(-4)	0.106661	0.136565	0.756675	-0.783021*	0.014786	0.092883
LnNO(-1)	0.040511*	0.228857*	0.040791	-0.034172	0.001623	0.369158*
LnNO(-2)	0.025390	0.167020	0.086295	0.081769	0.025983	0.213911*
LnNO(-3)	0.019092	0.087586	-0.035929	-0.174946	-0.004804	-0.113480
LnNO(-4)	-0.003400	-0.069783	-0.080899	0.081564	0.018971	0.326967*
C	0.339550*	0.218069	0.959330	1.149692	0.334557*	1.979932*
Full LVAR model Statistics:						
AIC: -23.51084		SCI: -19.95016		No. of Coefficients: 150		
LnST Equation Statistics:						
R^2:	0.991742	AIC:	-6.211192			
SSE:	0.008857	SCI:	-5.617746			
F-statistic:	455.3759					

Notes: * = 5% significant , SSE: Sum of Squared Errors

From the estimation results of the VAR model, the total number of 150 coefficients are estimated through the model. The model fit statistics for the full VAR system are represented for AIC and SCI as -23.51084 and -19.95016, respectively. The statistics for the LnST equation are estimated as R^2 = 99%, which means that 99% of the changes in LnST is explained by its own lags along with the explanatory variables' lags as well. The F-statistics for the LnST equation is relatively large, which shows the predictive capability of the model. For the model fit statistics in the LnST equation, the Sum of Squared Errors (SSE), that measures the in-sample forecast accuracy of the model by subtracting the actual and predicted values of the variable as squared values is estimated. Also, similar to the full model, the AIC and SCI model fit measures are estimated as -6.211192 and -5.617746.

As an alternative to the LVAR model for the cointegrated variables, the more sophisticated VEC model is used by reducing the optimal lag length by one due to the differencing process for the variables, as VEC (3). The results of the estimation for the VEC (3) model are reported in Table 8. The Number of the coefficients that are estimated in the VEC model is 138, including the ECT. The negative ECT shows the speed of the convergence to the long-run or equilibrium relationships, which is defined by coint.Eq.1 and Cointeg.Eq.2 in the table, as 13.5% and 6.8% per month [4]. Also, it is revealed that ECT for both cointegration equations in the LnST equation is significant at a 5% confidence interval, which is consistent with the findings in the Johansen test.

With the help of the cointegration equations in the VEC model, which are re-written as equations 4.1 and 4.2, it is possible to investigate the adequacy of the economic theory that exists through the long-run dynamics.

$$\Pi_{y_{t-1}} = -0.135(\mathrm{LnST}_{t-1} + 0.026\mathrm{LnIO}_{t-1} - 0.094\mathrm{LnCO}_{t-1} - 0.687\mathrm{LnIM}_{t-1} + 0.114\mathrm{LnNO}_{t-1}) \quad \textbf{(4.1)}$$

$$\Pi_{y_{t-1}} = -0.068(\mathrm{LnSC}_{t-1} - 0.122\mathrm{LnIO}_{t-1} + 0.067\mathrm{LnCO}_{t-1} - 0.485\mathrm{LnIM}_{t-1} - 1.03\mathrm{LnNO}_{t-1}) \quad \textbf{(4.2)}$$

Shoesmith (1995a) describes the interpretation of the cointegration equations, which, as a summary, declares that each sign represents the opposite effect in the equation. Where the negative sign demonstrates the direct relationship with the target

[4] For specific explanation about ECT see: (Granger and Lee 1989)

variable, the positive sign proves a reserved relationship. The LnIM has a negative sign in both equations that remarks its direct relationship with the LnST, which it means an increase in LnIM triggers the increase in LnST as well. the positive relationship between import prices and domestic steel prices has been proved in the previous studies (Liebman 2006). The remaining variables as LnIO, LnCO, and LnNO have different signs in each equation in which each variables' coefficient in one equation corrects the corresponding coefficient in other equations. In this case, since the related coefficients to each variable in both equations are greater in negative values (e.g., for LnIO, +0.026> -0.122), so it can be concluded that all the variables have a direct and positive relationship with the LnST. Besides the LnIO and LnCO, which seems logical to have a positive relationship with LnST as raw materials, the LnNO, which represents the increasing demand, also, can have a positive relationship like any other commodity in the literature.

From the table below, the row with the differenced variables demonstrates the left side of the equation, and the first column represents ECT alongside variable lags, which are included in the model as the right side of the equation for the specific variable defined in the first row. The (C) is the intercept term belongs to the corresponding equation as well.

Table 8 VEC (3) Estimation Results

Coefficients Estimation and p-values:

Cointegration Equation	**Coint.Eq. 1**	**Coint. Eq. 2**				
LnST(-1)		1.000000	0.000000			
LnSC(-1)		0.000000	1.000000			
LnIO(-1)		0.025911	-0.121872			
LnCO(-1)		-0.094042	0.067383			
LnIM(-1)		-0.686787	-0.484685			
LnNO(-1)		0.114455	-1.030131			
C		-1.841070	2.792718			
Variables:	**ΔLnST**	**ΔLnSC**	**ΔLnIO**	**ΔLnCO**	**ΔLnIM**	**ΔLnNO**
Coint.Eq.1	-0.134973*	-1.102647*	-0.629547	-0.121859	-0.054746	-0.679912*
Coint.Eq.2	-0.068170*	-0.583713*	-0.213622	0.086594	-0.053447*	0.088090
ΔLnST(-1)	0.247413*	-0.762430	-0.457816	0.351921	0.079183	0.804306
ΔLnST(-2)	0.052072	0.351190	0.620779	-0.321628	-0.086867	-0.244061
ΔLnST(-3)	0.130786	0.999804	0.892661	-0.293070	0.035463	0.435880
ΔLnSC(-1)	0.137971*	0.553837*	0.360253	0.050021	0.114064*	0.101324
ΔLnSC(-2)	0.058781*	0.221770	0.356499	-0.065359	0.150791*	-0.014914
ΔLnSC(-3)	0.022782	0.216198	0.133406	0.214065	0.092959*	0.077439
ΔLnIO(-1)	-0.018605	0.133481	0.087917	0.079068	0.015497	0.033462

Table 8. (Continue.) VEC (3) Estimation Results

Variables:	ΔLnST	ΔLnSC	ΔLnIO	ΔLnCO	ΔLnIM	ΔLnNO
ΔLnIO(-2)	0.006884	-0.034832	-0.409766*	-0.017851	0.005529	-0.032219
ΔLnIO(-3)	-0.022493	-0.041389	-0.080108	-0.052486	0.013460	0.157060*
ΔLnCO(-1)	0.037804*	-0.013648	0.360805*	0.223490*	-0.012443	-0.025096
ΔLnCO(-2)	0.000614	0.109979	-0.031470	-0.151990	0.030225	0.060695
ΔLnCO(-3)	0.013675	-0.063046	0.292186	0.115916	0.067735*	-0.023375
ΔLnIM(-1)	0.140776	0.451956	-0.672355	-1.233815*	0.057439	-0.917208*
ΔLnIM(-2)	0.007712	-0.818100	-0.240556	0.529046	0.154138	-0.203260
ΔLnIM(-3)	-0.097049	-0.151601	-0.800548	0.699836	-0.003421	-0.075964
ΔLnNO(-1)	-0.023582	-0.226400	-0.072890	0.035632	-0.045698	-0.451405*
ΔLnNO(-2)	0.000747	-0.050778	0.041684	0.100852	-0.012187	-0.222274*
ΔLnNO(-3)	0.015390	0.046457	0.030127	-0.076221	-0.016703	-0.331866*
C	0.000652	0.002148	-0.005857	0.003225	2.99E-05	0.012985*
Full VEC model Statistics:						
AIC: -23.34098		SCI: -20.06515		No. of Coefficients: 138		
LnST Equation Statistics:						
R^2:	0.742321	AIC:	-6.175226			
SSE:	0.009837	SCI:	-5.676732			
F-statistic:	13.68378					

Notes: * = 5% significant, SSE: Sum of Squared Errors

From the results of the VEC model estimation, the full model's AIC and SCI are -23.34098 and -20.06515, respectively. The R^2 for the LnST equation in the VEC model means that the differenced variables as short-run dynamics, in addition to ECT as long-run dynamics for explanatory variables, describe 74.2% of the changes in the LnST variable. Also, the AIC and SCI are defined as -6.175226 and -5.676732 as well.

D. Models Diagnosis

The residuals of each model have to be checked to be stationary and pattern-less for the model validation purpose. Thus, the diagnosis tests for serial correlation and heteroscedasticity are applied to the models' residuals as the most critical problems address the model misspecification.

In order to reveal the serial correlation or the autocorrelation in the residuals, firstly, the graphical method of the autocorrelation is applied for the LnST equation in both VAR and VEC models as the Figure 2 and 3. Secondly, the statistical *Breusch–Godfrey LM* test is utilized to be confident about the absence of the serial correlation in the residuals. The null hypothesis for the LM test is no serial correlation, which means if the null hypothesis cannot be rejected, then there is no serial correlation in the residuals. the LM test is one of the most powerful tests to detect serial correlation, often used in the literature.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.001	-0.001	0.0002	0.989
		2	0.016	0.016	0.0311	0.985
		3	-0.045	-0.045	0.2726	0.965
		4	-0.016	-0.016	0.3034	0.990
		5	-0.016	-0.015	0.3369	0.997
		6	-0.172	-0.174	4.0367	0.672
		7	-0.150	-0.157	6.8760	0.442
		8	-0.013	-0.017	6.8989	0.548
		9	-0.027	-0.044	6.9913	0.638
		10	-0.048	-0.077	7.2878	0.698
		11	0.114	0.104	8.9769	0.624
		12	-0.041	-0.079	9.1978	0.686
		13	-0.048	-0.125	9.4990	0.734
		14	0.056	0.038	9.9271	0.767
		15	-0.218	-0.261	16.343	0.360
		16	-0.036	-0.111	16.521	0.417
		17	-0.048	-0.038	16.840	0.465
		18	-0.001	-0.053	16.840	0.534
		19	0.108	0.038	18.483	0.490
		20	0.000	-0.021	18.483	0.556
		21	-0.079	-0.197	19.384	0.561
		22	0.067	-0.083	20.029	0.581
		23	0.010	-0.060	20.043	0.639
		24	0.033	-0.054	20.203	0.685
		25	-0.005	-0.068	20.207	0.736

Figure 2: ACF and PACF for LnST Equation Residuals in the LVAR model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.031	-0.031	0.1130	0.737
		2	0.010	0.010	0.1261	0.939
		3	-0.047	-0.047	0.3946	0.941
		4	-0.031	-0.034	0.5135	0.972
		5	-0.041	-0.043	0.7245	0.982
		6	-0.197	-0.202	5.5480	0.476
		7	-0.132	-0.157	7.7458	0.356
		8	0.041	0.022	7.9560	0.438
		9	0.005	-0.017	7.9593	0.538
		10	-0.010	-0.047	7.9730	0.631
		11	0.170	0.152	11.738	0.384
		12	0.013	-0.021	11.759	0.465
		13	0.003	-0.062	11.760	0.547
		14	0.106	0.128	13.265	0.506
		15	-0.193	-0.186	18.306	0.247
		16	-0.022	-0.054	18.370	0.303
		17	-0.070	0.009	19.044	0.326
		18	-0.012	-0.001	19.064	0.388
		19	0.105	0.087	20.619	0.358
		20	-0.012	0.032	20.641	0.419
		21	-0.094	-0.160	21.914	0.404
		22	0.090	-0.002	23.102	0.396
		23	0.003	0.012	23.103	0.455
		24	0.033	0.010	23.264	0.504
		25	-0.018	-0.010	23.312	0.559

Figure 3: ACF and PACF for LnST Equation Residuals in the VEC model

As observed from the Figure 2 and 3, the p-values of the ACF and PACF for the first 25 lags are insignificant which is delineated as no serial correlation in the residuals of the equation for the LnST in both the VAR and VEC models.

The results of the *Breusch–Godfrey LM* test are reported in Table 9 for the full LVAR and VEC model. The test is applied for 5 lags, which is enough to identify any serial correlation in the residuals. The accumulated p-value for the 5 initial lags is greater than the 5% significance level, which means that the null hypothesis of no serial correlation cannot be rejected. However, the result of the LM test is supported by the results of the ACF and PACF graphically.

Table 9 The Result of the LM Test for LVAR and VEC Residuals

Null Hypothesis: No Autocorrelation at lags 1 to h				
	LVAR		VEC	
Lag	F-Stat	Prob.	F-Stat	Prob.
1	0.995453	0.4805	1.059222	0.3812
2	0.991408	0.5021	1.070805	0.3353
3	1.004051	0.4778	0.933314	0.6623
4	0.973368	0.5688	0.947213	0.6444
5	1.155735	0.1293	1.048495	0.3511

As another aspect of the model validation process, the presence of heteroscedasticity is problematic as well. The heteroscedasticity refers to the escalating variance in the model residuals, which is in contrast with the homoscedasticity situation, which is an essential assumption in the econometric models. In this study, to detect heteroscedasticity, since the graphical methods are confusing and hard to interpret, the *Breusch-Pagan-Godfrey* test is used. The null hypothesis for this test is in favor of homoscedasticity, in which the failure to reject the null hypothesis proves the absence of heteroscedasticity in the residuals. The results of the test for heteroscedasticity are printed in Table 10.

Table 10 The Result of the Heteroscedasticity Test for LVAR and VEC Residuals

Null Hypothesis: Homoscedasticity in the Residuals		
	LVAR	VEC
Chi-Sq.	1039.149	899.7075
Prob.	0.2415	0.0750

From the results, the related p-values to the Chi. Square statistics in the heteroscedasticity test for both models are greater than the 5% significance level, which is defined as the failure to reject the null hypothesis of homoscedasticity. Thus there is no heteroscedasticity in the residuals.

It can be concluded that models are appropriately fitted to the data, Considering the successful validation of the models.

E. IRF Analysis

The IRF analysis helps to reveal the impulses that are made by explanatory variables as LnSC, LnIO, LnCO, LnIM, and LnNO and the responses of the target variable as LnST to these impulses. With the VAR or VEC models, it is possible to assess all variables impulses to each other. Therefore, in this study, only responses that are related to the LnST are assessed since it is the variable of interest. The IRF for the LVAR and VEC models are visualized accordingly in Figures 4 and 5.

For both the LVAR and VEC model's IRF graph, each variable impulses on the LnST responses against the months are estimated. In the VAR model, except for LnST and LnIO, all the responses have increasing and positive behavior. However, for the LnSC, the response takes the maximum value in the 3rd period, which then starts to decline until the 7th period, which again starts to increase until the 13th period, which then slightly begin to decrease, and after the 25th period, it shows the negative and decreasing behavior. For the LnCO, LnIM, and LnNO, the increasing and positive value continues until the 14th, 9th and 5th periods, accordingly, which then they start to decrease. For LnST as its own lag, the response starts with a decreasing pattern, which after 5 periods it demonstrates the negative and decreasing behavior, which then recovers after the 30th period. The LnIO starts in decreasing and negative response, which tends to the positive value after 2 periods and maximizes around the 3rd period, which after some fluctuations, starts to rise after the 10th period towards positive and increasing response.

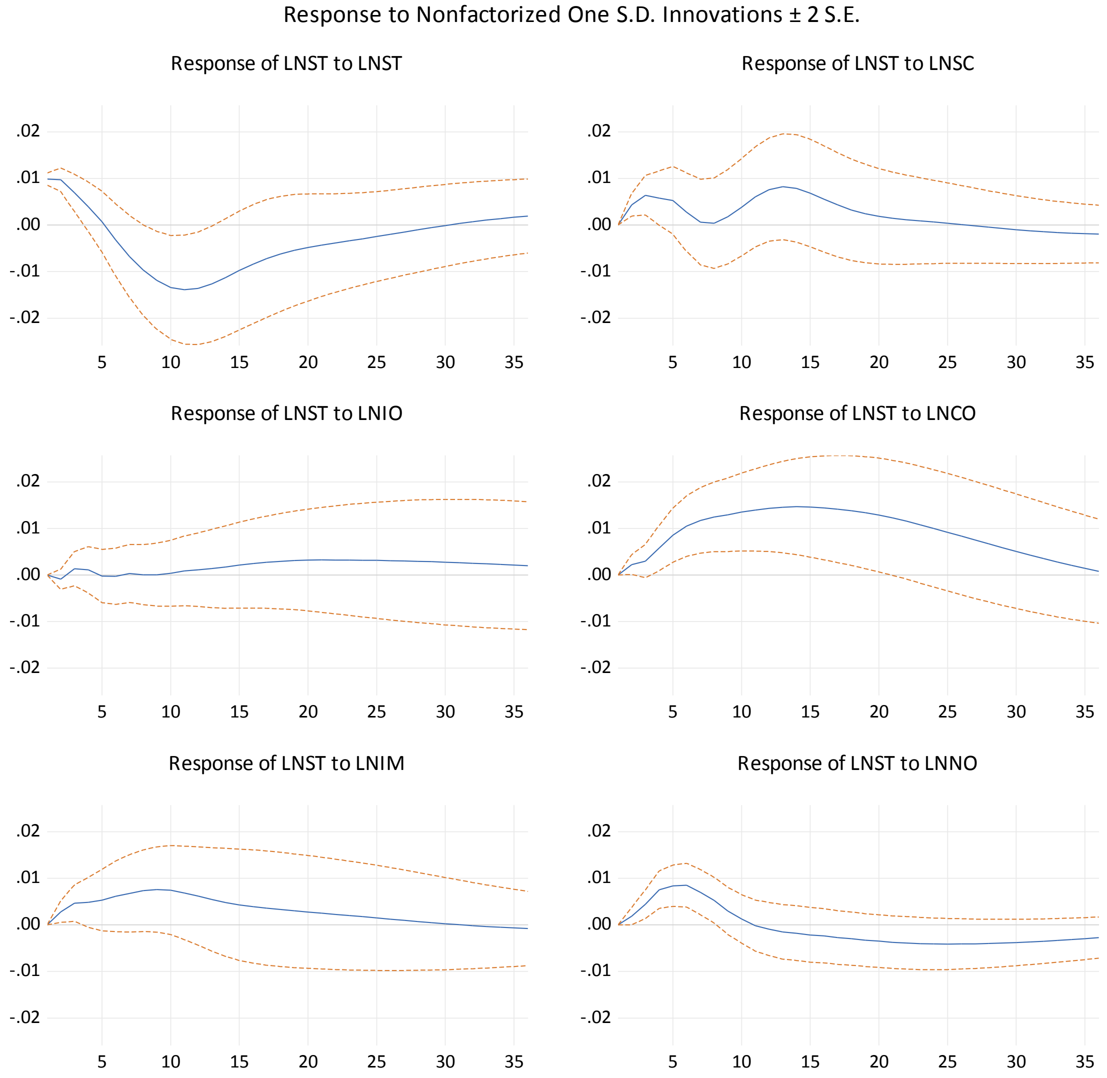

Figure 4: IRF for the LVAR model

Investigating the IRF for the VEC model, it is disclosed that all the responses except the LnIO have an increasing and positive value. Also, the LnIO, after the first lag, tends to constant growth and positive value. The LnST lag is increasing until the first lag, which is then starting to decrease, and after the 7th period, it shows a constant negative value. For LnCO and LnIM, the increasing patterns are continuous and positive. The LnSC and LnNO both have a rising response until the 2nd and 5th periods, respectively, which is then the LnSC is decreased slightly to the region of the negative value until it recovers after the 12th period. The LnNO starts to decreases after the 5th period until the 11th period, which continues to fluctuate around the baseline.

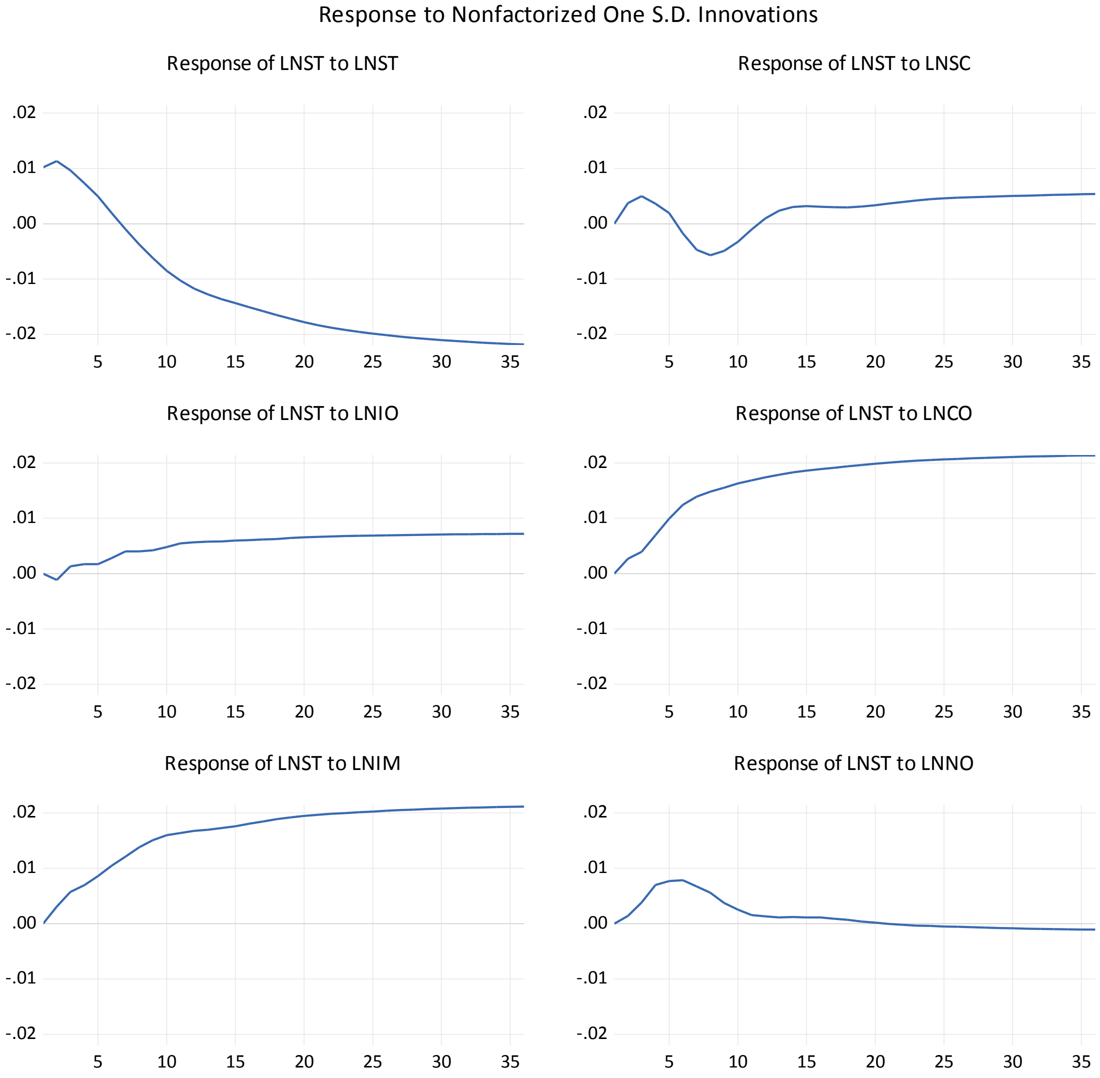

Figure 5: IRF for VEC model

Despite the similar patterns in the IRF in the short-run for both models, in the long-run, the situation is different. While in the LVAR model, responses tend to the baseline, in the further lags and the effect of the impulses are dumped after initial periods, the responses in the VEC model seem to be stabilized at a constant level after the initial fluctuations. The difference of the IRF in the two models is initiated from the structure of the VEC model, which includes the long-run (equilibrium) dynamics. As a reason, the long-run relationship is illustrated as stabilized responses of the LnST. The findings of the IRF, in this case, are consistent with the results of the study, which was done by (Naka and Tufte 1997).

F. FEVD Analysis

Similar to the IRF for the VAR and VEC model, only the FEVD, which is related to the LnST, is taken under the assessment. The FEVD is estimated for 18 periods and shows the contribution of the explanatory variables to predict the LnST. The Results of the FEVD estimation for the LVAR and VEC models are reported in Tables 11 and 12, accordingly.

Table 11 The FEVD of LnST for LVAR Model for 18 Months

Coefficients Estimation and p-values:

Mo	S.E.	LnST	LnSC	LnIO	LnCO	LnIM	LnNO
1	0.009866	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.017403	83.99795	10.57289	0.010539	2.294934	2.197771	0.925918
3	0.024236	66.60084	20.96578	0.983612	3.773583	4.463780	3.212410
4	0.030148	52.46935	25.00600	1.864989	7.964078	5.487910	7.207672
5	0.035254	41.53361	26.47157	2.067392	13.69895	6.314666	9.913808
6	0.039507	33.32805	25.32811	2.409302	19.85160	7.388136	11.69480
7	0.043184	28.15274	23.15064	2.979397	25.36868	8.409997	11.93854
8	0.046717	25.30714	21.15642	3.282984	29.71999	9.285748	11.24772
9	0.050191	24.03885	19.83575	3.444037	32.79325	9.856085	10.03203
10	0.053810	23.41677	19.25380	3.603569	34.92926	10.02324	8.773370
11	0.057444	22.85454	19.44115	3.835983	36.35295	9.816344	7.699037
12	0.061001	22.12290	20.07575	4.084390	37.44613	9.425378	6.845453
13	0.064289	21.27345	20.73124	4.377169	38.43849	8.970898	6.208759
14	0.067228	20.39996	21.11462	4.722686	39.48339	8.543793	5.735556
15	0.069788	19.57295	21.15350	5.143849	40.55828	8.171098	5.400321
16	0.072018	18.82370	20.89972	5.610223	41.64826	7.858769	5.159338
17	0.073969	18.15980	20.46071	6.104106	42.68395	7.590947	5.000495
18	0.075703	17.57465	19.93327	6.594779	43.64035	7.358187	4.898773

The first column after the month numbers shows the Standard Error (S.E.) that indicates the deviation of the sample mean from the population mean, which in simple terms show the accuracy of the measurement of the statistics. The numbers in decimals should multiply by 100, so they can be read as a percentage to facilitate the interpretation.

In the LVAR model FEVD for the first period, only the LnST's own lag has the power to predict the LnST. However, after the first period, all other variables lags have the predictability power on the LnST, and as a result, the proportion of the LnST's own lag has decreased. For 7 periods, it is observed that the LnSC has the largest share in forecasting the LnST, which after the 7th period, the LnCO has the largest portion until the 18th period. It is concluded that the most important variables to forecast LnST besides its own lags are the LnST and LnCO as explanatory variables.

The FEVD for the VEC model shows that only LnST's own lag has a role in predicting LnST in the first period, as in the LVAR. The LnSC has the most considerable amount until the 5th period, which after that, the LnCO has the largest proportion until the 18th period. With Consideration to results, besides the LnCO as the most crucial variable to predict LnST, all the variables take a considerable share in predicting LnST, except the LnNO, which has the less portion.

Table 12 The FEVD of LnST for VEC Model for 18 Months

Coefficients Estimation and p-values:

Mo	S.E.	LnST	LnSC	LnIO	LnCO	LnIM	LnNO
1	0.010176	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.018417	87.22916	7.491106	0.018666	2.483252	2.302595	0.475225
3	0.026045	72.75141	14.42326	1.102497	4.309908	5.413671	1.999256
4	0.032925	60.08480	16.37947	2.417880	8.514050	7.704791	4.899011
5	0.039111	49.98739	16.05548	3.506175	13.88007	9.966903	6.603974
6	0.044716	41.13086	13.95695	5.136848	19.64172	12.57878	7.554837
7	0.049831	33.91238	11.71631	7.017982	24.60093	15.19258	7.559816
8	0.054700	28.27171	9.979433	8.274611	28.52948	17.82873	7.116037
9	0.059401	23.97432	8.796237	9.189257	31.50486	20.18108	6.354246
10	0.064214	20.58779	8.156086	9.992315	33.70210	22.00009	5.561621
11	0.069141	17.92866	8.133271	10.74359	35.16408	23.19254	4.837852
12	0.074215	15.80340	8.624136	11.28003	36.13312	23.93512	4.224192
13	0.079323	14.11989	9.371565	11.65983	36.78178	24.35368	3.713253
14	0.084424	12.78737	10.12864	11.92609	37.25130	24.61210	3.294499
15	0.089442	11.74708	10.76882	12.14600	37.58502	24.80535	2.947724
16	0.094373	10.94407	11.25729	12.30956	37.83137	24.99895	2.658761
17	0.099199	10.33318	11.62253	12.43976	38.00378	25.18825	2.412501
18	0.103958	9.870646	11.90764	12.53740	38.12009	25.36416	2.200063

A comparison between the LVAR and VEC models' FEVD analysis shows that in the LVAR model, the share of the LnST's own lags on predicting LnST is greater than the VEC model. In contrast, in the VEC model, explanatory variables have more share in predicting LnST comparing to the LVAR model. In both models, the LnCO has substantial forecast power in the long-run as an explanatory variable.

G. Forecast Results and Discussion

After models are validated, they can be used for the forecast. In the forecasting process, two procedures are used frequently. The *In-Sample* procedure uses all the data points to make the model, and for the subsequent forecast(s), there will be no actual values out of the model making process to compare and measure the accuracy of the forecast. In this situation, only the actual values which are used to make the model are compared to fitted values that are generated using the same models. Thus, the in-sample procedure does not reflect the real-world setting.

The other procedure which is used in this study is the *out-of-sample* or *hold-out*. The purpose of the out-of-sample procedure is to test the forecast capability of the models regarding the real-world setting. It is done by comparing the forecast models' outcome against the actual values which remain out of the modeling process. As mentioned before, the data from January 2009 to December 2018 are used to make the models. The actual values kept out of the modeling process are from January 2019 to June 2020, which equals to forecast horizon of 18 months. In the LVAR and VEC systems, due to the use of lagged versions of all variables, there is no need to forecast each explanatory variable separately with the univariate models. The data from time (t-1) are used to forecast time (t). Consequently, for the time (t+1) forecast, the data from time (t) are used. For multiple-step forecast as here, first, a one-step-ahead forecast is performed, then using this forecasted value, other steps are forecasted in the same manner for each variable. The results of the 18 months out-of-sample forecast starting from January 2019 by the LVAR and VEC models, along with the actual values, are visualized in Figure 6 and Table 13. Also, to demonstrate the usefulness of suggested models in practice, true forecasts for 4 months from July 2020 until December 2020 are printed without any assessment in Figure 6 and Table 13.

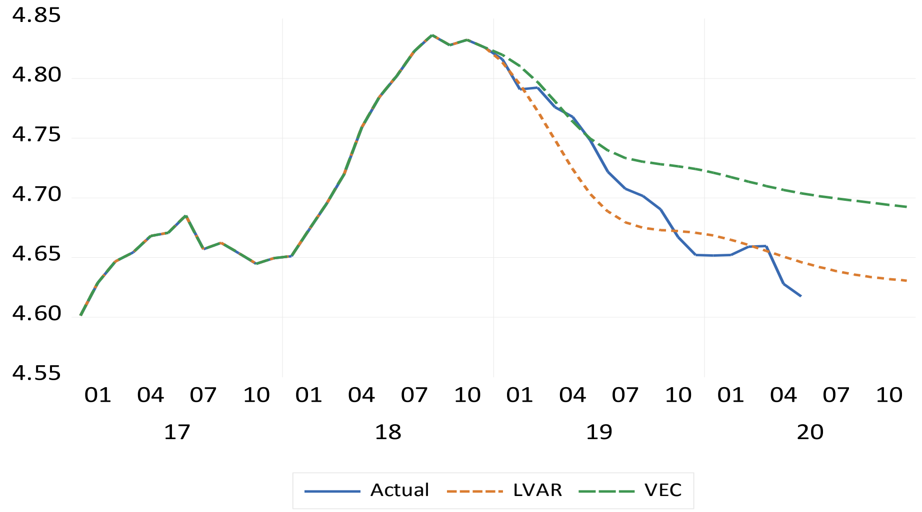

Figure 6: Forecast Results from Jan.2019 to Dec.2020

Table 13 Forecast Result values for 18 months

Months	Actual	LVAR	VEC
2019M01	4.816160	4.813718	4.819777
2019M02	4.790935	4.795106	4.810418
2019M03	4.792327	4.772910	4.797050
2019M04	4.775960	4.748642	4.780852
2019M05	4.767913	4.724113	4.763935
2019M06	4.748234	4.703314	4.749569
2019M07	4.721710	4.688623	4.739618
2019M08	4.707674	4.679337	4.733348
2019M09	4.701598	4.674866	4.730124
2019M10	4.690362	4.672866	4.728067
2019M11	4.666978	4.671998	4.726380
2019M12	4.652148	4.670676	4.724065
2020M01	4.651614	4.668362	4.721038
2020M02	4.652148	4.664745	4.717313
2020M03	4.659061	4.660347	4.713497
2020M04	4.659591	4.655458	4.709820
2020M05	4.627842	4.650623	4.706602
2020M06	4.617399	4.646029	4.703790
2020M07	N/A	4.641997	4.701437
2020M08	N/A	4.638541	4.699361
2020M09	N/A	4.635754	4.697512
2020M10	N/A	4.633523	4.695735
2020M11	N/A	4.631847	4.694033
2020M12	N/A	4.630609	4.692345

For better visualization of the forecasted period, the graph is reported from January of 2017. Both forecast outcomes of the models can be able to catch the downward trend in the actual series. However, the VEC model result looks to overestimate, especially after the 4th period of the forecast. On the other side, the LVAR model underestimates the forecast for the 10 periods, which is then slightly beginning to overestimate. Although both models seem to forecast reasonably, the LVAR model presents better performance. The results of the forecast accuracy measure in terms of RMSE and MAPE are reported in Table 13.

Table 14 Forecast Accuracy Measures for LnST

	LVAR	VEC
RMSE	0.023766	0.047488
MAPE	0.423052%	0.804208%

Notes: MAPE in Percentage, RMSE: Same level as variables

The RMSE and MAPE accuracy measure are estimated based on the accumulated forecast errors for 18 months. The RMSE and MAPE values show the twice more accurate result for the LVAR model, comparing the VEC model. The value for the LVAR model's RMSE is 0.23766, which is half of the VEC model's RMSE of 0.047488. Also, the MAPE for the LVAR model with 0.423052% is around 50% lesser than the MAPE for the VEC model, with 0.804208%.

From the results of the comparison in terms of the forecast accuracy measure, it is evident that the LVAR model outcome for 18 months' forecast is better than the VEC model outcome for the same forecast horizon. When looking into the literature on comparison of the LVAR and VEC models performance in forecasting financial series, we found confusing and debatable results.

Engle & Yoo (1987) have used some simulations to compare the forecast performance of the LVAR and VEC models. As a result, they proved the superiority of the VEC model over the LVAR model in the cointegrated series. Also, Hoque & Latif (2006) attempted to forecast the exchange rate of the Australian dollar based on the USD dollar using LVAR, *Bayesian VAR* (BVAR), and VEC models. The result of the analysis demonstrates that the VEC model outperforms the LVAR and BVAR models for the 11 months' length forecast.

Besides studies with the contradiction to our findings, some studies manifest confusing and mixed results as well. Hoffman & Rasche (1996) assessed the forecast performance of the *Differenced VAR (DVAR)*, LVAR, and VEC models using money demand, fisher equation, and interest rate variables. Their results suggested a slight decline in the *Mean Square Error (MSE)* measure in forecasting with the VEC model over the other models for the particular time-span. However, generally, the results of the relative forecast performance of the three models are unclear and mixed.

Clements & Hendry (1995) tried to investigate and compare the forecast performance of the cointegrated variables with the DVAR, LVAR, and EC models using the bivariate system. In this study, the Monte Carlo analysis applied to the accumulation of the results as well. Although the results are not clear, they suggest that the variable selection, forecast horizon, and cointegration rank are essential factors to determine these three models' behaviors and forecast performance.

One of the supportive studies for our findings is the work done by Suharsono, Aziza, & Pramesti (2017). They attempt to model the Indonesian stock market index using LVAR and VEC models. Since they aimed to define the best model to investigate the market index, they did not perform an out-of-sample forecast. The study is concluded as the LVAR model outperforms the VEC model in terms of model fit statistics.

The main study that supports our findings is Fanchon & Wendel's (1992) study, which has tried to forecast the cattle prices using LVAR, BVAR, and VEC models. They perform out-of-sample forecasting for a 58 months' horizon. Excluding BVAR, which performs the worst performance, comparing the LVAR and VEC models reveals that the LVAR model outperforms the VEC model for the first 45 months, which then slightly generates smaller errors. However, cumulative MSE is smaller than the VEC model.

Fanchon & Wendel (1992) and Clements & Hendry (1995) gave some insights into the reasons that the LVAR model outperforms the VEC model. These are including, the lag length used in the models, which affects the short-run dynamics duration, which as a result, can make the LVAR model to forecast more accurately (Fanchon and Wendel 1992). The variable selection when the variables have a shorter memory and drive the LVAR model to perform a better forecast. The forecast horizon is another critical issue to define the performance of the models. However, it seems that the VEC model can be more favorable in the long-term forecasts comparing to the VAR models, which should be taken under careful consideration to determine the duration of the long-term forecasts.

V. SUMMARY AND CONCLUSION

The current study aims to find suitable models to perform multivariate forecasting of the steel price movements in terms of reliability and practicality. For this purpose, the related financial leading indicators in the steel industry are reviewed and nominated from the dedicated literature. The range of the data is from January 2009 to June 2020. The modeling process is conducted under the VAR and VEC systems with the data from January 2009 to December 2018, which makes it possible to perform out-of-sample forecasting. All the variables are indexed as January 2009 =100 and transformed with the natural logarithm to control the variable stability.

The preliminary analysis of the data starts with the stationarity test by the ADF procedure, which discloses the integration order of the variables to be I (1) that is essential for variables to be modeled by the VAR and VEC models. The next step is to check the variables' adequacy to be useful to predict the target variable. This is done by checking the Pearson Correlation matrix and bivariate Granger Causality analysis. After finding out that all selected variables are suitable to include in the model, the model making process starts with defining optimal lag length for the VAR model. The optimal lag length is determined by the minimization of the AIC, which is found to be (4) for the unrestricted VAR model. Consequently, the Johansen test procedure is applied to detect the cointegration relationship between variables to be used in the VEC model with the optimal lag length of the (3) due to the differencing. Following the identification of the two cointegration relationships, the LVAR and VEC model is suggested to fit the data. The models are validated by checking the serial correlation and heteroscedasticity problems in the residuals to avoid model misspecification.

The IRF and FEVD analysis after the model-making process illustrate the behaviors of the models, which can give an idea about the short-run and long-run characteristics of the models.

The forecast validation exercise is practiced through the out-of-sample procedure for 18 months, starting from January 2019. The results of the forecast reveal that while both models yield convincible results, the LVAR model gets smaller RMSE and MAPE values by half than the VEC model. Although the results are not compatible with some previous studies which claim the superiority of the VEC models, some other studies support the results, assuredly. The underlying reason for miscellaneous results of the forecasting performance in different studies might be generated from the characteristics of the variables, the lag length, and the duration of the forecast horizon.

To conclude, this study enforces the potential use of the LVAR and VEC models to forecast the prices of the steel products in a multivariate system. The suggested models in this study can be used in organizations related to the steel industry owing to their simple methodology.

The results of the analysis show that the LVAR model performs better than the VEC model in forecasting steel products on the mid-term horizon. In long-term forecasting, this result might not be applicable. However, the outcomes of the study should be investigated attentively due to the inherent uncertainty in forecasting models.

A comprehensive study can be done to overcome forecasting uncertainties in the future, considering the various financial variables, different structures, and testing for various forecast horizons to reach reliable and trustworthy results. As a future aspect of this study, the multivariate vector models (e.g., VAR, VEC) can be combined with novel data-driven models such as the ANN algorithms, which are called *Hybrid* models, to achieve better forecasting performance.

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