# Chinese steel production and shipping freight markets: A causality analysis

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**Abstract**
*This paper provides statistical evidence in support of the view, widely held in the dry industry, that there is a lead-lag relationship between Chinese steel production and dry bulk freight rates. Furthermore, this raises an important question about the direction of their relationship. Despite the plethora of studies on micro and macro economic determinants of freight rates, there have been no studies addressing these issues. Hence, this paper undertakes such an investigation using Co-integration analysis, VAR based Granger Causality tests and Impulse Response analysis. Another contribution is that we apply our methodology separately to the spot and period freight markets, and empirically examine and analyze the differences among the causal relationships of four different vessel categories. The results are generally in line with industry expectations and contribute to the understanding of commodity and freight market movements.*

## 1. Introduction

In recent times, China has developed into the major iron ore importer, while its steel industry accounts for over 50% of world steel production. At the same time, the dry bulk freight market has largely been moving on the back of Chinese iron ore imports – the basic component of steel. In this context, it is interesting to investigate how China's steel output interacts with the entire dry cargo market.

An abundance of research has been done to establish the key economic drivers of freight rates. For example, Zanettos (1966) adopted a structural approach to investigate the relationship between time charter rates and a set of variables, including London Interbank Offered Rate (LIBOR), oil price, Air (index for air transportation), tonnage in lay up, tonnage scrapped and Operating Expenses (OPEX). Strandenes (1984), and Beenstock and Vergottis (1989, 1993) find that the freight rates are determined by macroeconomic factors such as oil prices, world economic activity, the growth of industrial production, commodities trade, as well as by internal factors, such as newbuilding ship orders, deliveries and demolitions.

In another study, Kavussanos and Nomikos (2003) perform causality tests and impulse response analysis to investigate the relationship between futures and spot prices in the freight futures market. One year later, Haigh et al. (2004) implement Directed Acyclic Graphs (DAG's) and Error Correction Models to investigate the dynamics of the freight rates and routes that compose the Baltic Panamax Index (BPI) and they find that the index may not be appropriately weighted.

Dikos et al. (2006) use system dynamics modeling and look at causality effects, to assess the macroeconomic factors that determine the tanker time charter rates. They determine the flow of supply of tonnage through entry, exit and lay-up decisions and they compare it with the demand. Finally from their interaction they determine the key factors that affect tanker rates. Yu et al. (2007) employ co-integration analysis and algorithms of inductive causation on directed acyclic graphs to examine the relationship between US grain and freight markets and find significant dynamic relationships. In addition, Poulakidas and Joutz (2009) examine how a spike in oil prices affect tanker rates. Their analysis of the lead-lag relationship between crude oil prices, crude oil inventories and tanker rates is based on co-intergration and Granger causality, and their results are indicative of significant lead-lag relationships.

However, there is a gap in the literature, as there have been no comprehensive studies attempting to determine the underlying relationship between these variable at an empirical level. The general consensus is that the level of steel production is a bellwether of the demand for raw materials and, consequently, of freight rate fluctuations; though, so far this has only a theoretical grounding. Hence, the current paper intends not only to cover this gap, but also assess the relations in the context of both the spot and period charter market for four different vessel sizes (i.e. Capesize, Panamax, Supramax and Handysize).

The aim of this paper is to examine the relationship between Chinese crude steel output and dry bulk freight rates. For this purpose, we employ contemporary and sound econometric techniques, such as Co-integration analysis, VAR based Granger Causality and Impulse Response analysis. More specifically, we apply our methods both on the spot and period market of each vessel category and we juxtapose and analyze the results.

The results are of interest to maritime practitioners and academics alike, as they shed some light on the interactions between steel production and freight rates.

The structure of the paper is as follows. Section 2 describes the methodology and presents the theoretical background. Section 3 discusses the data and their properties. Section 4 presents the empirical results, while section 5 concludes the paper.

## 2. Theoretical Framework

The lead-lag relationship refers to the situation where the values of a leading variable are linked to the values of a lagged variable at later times.

In our analysis, first of all, we need to test for unit roots performing the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Should all the series are found non-stationary, we have to examine the existence of co-integration, using the Johansen test. Then, we set up a VAR model in the levels of the data, determining the appropriate lags using various lag length criteria, such as the sequential modified LR test statistic (LR), the Final prediction error (FPE), the Hannan-Quinn information criterion (HQ), the Schwarz information criterion (SC) and the Akaike information criterion (AIC). After that, we check if the model is well specified by looking at its R-squared, and by applying the VAR Residual Serial Correlation LM test and the VAR Residual Heteroskedasticity Test. Based on this model, we test for Granger causality, employing Wald tests. Finally, we carry out Impulse Response (IR) analysis to determine if changes in one variable have a positive or negative effect on the other and how long this effect will last. It should be noted that if two variables are co-integrated, the IR analysis should be based on a VECM model and if not, on an unrestricted VAR.

### a) Co-integration

When two non-stationary time series are integrated of the same order and there is at least one stationary linear combination between them, then they are co-integrated and have a common stochastic drift. The co-integration implies the existence of a long run equilibrium relationship characterized by short run deviations.

In our study we adopt the Johansen test (1991, 1995) in order to test for co-integration.

**b) Unrestricted Vector Autoregression (VAR)**

The VAR framework models each endogenous variable as a function of its own lags and the lags of all other variables in the system. The VAR models can be employed as an appropriate econometric specification for investigating the relations between variables, such as the Granger causality, as they describe the joint generation process of the variables involved.
The mathematical representation of a VAR with n lags, VAR (n), is:

$$y_t = c + A_1 y_{t-1} + \ldots + A_n y_{t-n} + Bx_t + \varepsilon_t$$

Where c is a vector of intercepts, $A_i$ and B are matrices of coefficients and $\varepsilon_t$ is a vector of error terms which are uncorrelated with their own lags and there is no serial correlation in individual error terms.

**c) Vector Error Correction Model (VECM)**

The VECM is actually a restricted VAR, which is designed to capture the dynamic interrelationship between non-stationary but co-integrated variables. In this model, the variables are differenced and an error correction term (obtained from co-integration) is incorporated. This term accounts for the gradual short-run adjustment of the deviation from long-run equilibrium.
In our bivariate case the VECM can be written in the form:

$$\Delta y_t = b_{y0} + b_{y1}\Delta y_{t-1} + \ldots + b_{yn}\Delta y_{t-n} + \gamma_{y1}\Delta x_{t-1} + \ldots + \gamma_{yn}\Delta x_{t-n} - \lambda_y(y_{t-1} - a_0 - a_1 x_{t-1}) + \varepsilon_t^y$$

$$\Delta x_t = b_{x0} + b_{x1}\Delta y_{t-1} + \ldots + b_{xn}\Delta y_{t-n} + \gamma_{x1}\Delta x_{t-1} + \ldots + \gamma_{xn}\Delta x_{t-n} - \lambda_x(y_{t-1} - a_0 - a_1 x_{t-1}) + \varepsilon_t^x$$

where $y_t = \alpha_0 + \alpha_1 x_t$ is the long-run co-integrating relationship and $\lambda_\chi$ and $\lambda_y$ are the error correction parameters.

**d) Granger causality**

In the general sense, correlation does not necessarily imply causality. Therefore, we make use of the Granger (1969) approach. Granger causality, in the case of two variables, y and z is defined as follows:
"z is Granger-caused by y, if z can be better predicted using the lagged values of both variables, than by using only its own lagged values, or equivalently, if the coefficients of the lagged y's are statistically significant."
Mathematically, we test for Granger causality using the VAR model below:

$$z_t = a_0 + a_1 z_{t-1} + \ldots + a_n z_{t-n} + b_1 y_{t-1} + \ldots + b_n y_{t-n} + u_t$$

$$y_t = c_0 + c_1 y_{t-1} + \ldots + c_n y_{t-n} + d_1 z_{t-1} + \ldots + d_n z_{t-n} + v_t$$

$H_0$: $b_1 = b_2 = \ldots = b_n = 0$ (*y does not* Granger-cause *z*), against $H_1$: 'Not $H_0$'
and
$H_0$: $d_1 = d_2 = \ldots = d_n = 0$ (*z does not* Granger-cause *y*), against $H_1$: 'Not $H_0$'

According to Toda and Yamamoto (1995), in order to test for Granger causality, we have to set up a well specified VAR model in the levels of the data, regardless of the unit roots. Even if the data are non stationary (which is our case), we need to set up a VAR model in levels (as we would also do with stationary data), adding one extra lag (which we should not include also in the test formulation) in order to fix up the distribution of the Wald test in such a way as to be asymptotically chi-square distributed. Then we can perform the Granger causality tests and the results are reported in Table 3.

It should be noted that this VAR model in levels of I(1) data, is appropriate only for Granger causality. It should not be used for other purposes, such as IR analysis. Thus, in our IR analysis that follows, we shall use a VAR in first differences for those data which are non stationary but not co-integrated, and a VECM model for the co-integrated variables.

**e) Impulse Response (IR) Analysis**

IR analysis complements Granger-causality providing a further insight into the interactions between the variables under examination. In particular, it identifies the reaction of one variable with regard to an impulse to another, within a system that may involve a number of other variables as well. The impulse enters the system through a positive shock of one standard deviation to the residual and then an impulse response function traces the effect on the endogenous variables in the VAR model.

## 3. Data

We perform our analysis using the EViews software and we employ monthly data taken from Clarkson's Research Services Ltd (CRLS) database, which cover the period starting from January 1999 to July 2014. The dataset considers representative vessels of four separate categories: Handysize (10,000 - 39,999 dwt), Supramax - Ultramax (50,000 - 64,999 dwt), Panamax - PostPanamax (65,000 - 99,999 dwt) and Capesize (100,000+ dwt). Also, Clarksons provides historical average spot and trip rates for each vessel type. Thus, in our analysis we use these rates as representative of the spot market.

In addition, for the purposes of our analysis, we collect data (from CLRS database) for the Chinese crude steel production over the same time period.

## 4. Empirical Results

The KPSS unit root test is carried out on the log-levels and log-differences of the freight rates and Chinese steel production, for all vessel sizes, and tests the null hypothesis of stationarity under two different assumptions: First the series have an intercept, and second, a constant and a linear trend. The results, which are presented in Table 1, reject the null hypothesis in almost all cases of level forms suggesting that the series are non-stationary.

| | Log-Levels | | Log-first differences | |
|---|---|---|---|---|
| | Intercept | Const. & trend | Intercept | Const. & trend |
| ***Capesize*** | | | | |
| avg spot | 0.354555* | 0.329984*** | 0.143769 | 0.043076 |
| 6-m tc 170k | 0.419046* | 0.262273*** | 0.154757 | 0.062233 |
| ***Panamax*** | | | | |
| avg spot | 0.34391 | 0.332426*** | 0.154909 | 0.025768 |
| 6-m tc 75k | 0.276823 | 0.273947*** | 0.115373 | 0.037239 |
| ***Supramax*** | | | | |
| avg trip | 0.420360* | 0.267649*** | 0.172491 | 0.036858 |
| 6-m tc 52k | 0.318756 | 0.261730*** | 0.294308 | 0.044679 |
| ***Handysize*** | | | | |
| avg trip | 0.468322** | 0.139939* | 0.093198 | 0.09537 |
| 6-m tc 30k | 0.475894** | 0.335320*** | 0.225578 | 0.038353 |
| Ch_steel_pr | 1.611345*** | 0.389544*** | 0.25282 | 0.10718 |

*Notes:*
*** denotes rejection of $H_0$ at 1% level, **at 5% and * at 10%
$H_0$: the series is stationary, $H_1$: the series is non stationary
The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

**Table 1: KPSS test**

Since the variables are non stationary, we investigate the existence of co-integrating relations through the Johansen Co-integration. The results are presented below:

| Vessel Size | Pair of variables | Lags | Hypothesized No. of CE(s) | Trace | 0.05 CV (trace) | Max Eigenvalue | 0.05 CV (Max Eigen.) |
|---|---|---|---|---|---|---|---|
| *Capesize* | avg spot - Ch_steel_pr | 3 | None | 18.21567 | 20.26184 | 11.11145 | 15.8921 |
| | 6-m tc 170k - Ch_steel_pr | 2 | None* | 21.32890 | 20.26184 | 14.73266 | 15.8921 |
| | | | At most 1 | 6.59625 | 9.164546 | 6.596250 | 9.164546 |
| *Panamax* | avg spot - Ch_steel_pr | 3 | None | 18.00954 | 20.26184 | 12.68389 | 15.8921 |
| | 6-m tc 75k - Ch_steel_pr | 3 | None | 19.3286 | 20.26184 | 13.72006 | 15.8921 |
| *Supramax* | avg trip - Ch_steel_pr | 3 | None* | 21.26618 | 20.26184 | 13.58359 | 15.8921 |
| | | | At most 1 | 7.682594 | 9.164546 | 7.682594 | 9.164546 |
| | 6-m tc 52k - Ch_steel_pr | 3 | None | 18.95875 | 20.26184 | 12.34651 | 15.8921 |
| *Handysize* | avg trip - Ch_steel_pr | 2 | None | 11.42643 | 20.26184 | 6.38637 | 15.8921 |
| | 6-m tc 170k - Ch_steel_pr | 3 | None | 19.28369 | 20.26184 | 13.75657 | 15.8921 |

*Notes:*
* denotes rejection of the hypothesis at the 0.05 level.
The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series
The trace statistic tests $H_0$: r cointegrating relations against $H_1$: k cointegrating relations.
The max eigenvalue statistic tests $H_0$: r cointegrating relations against $H_1$: r+1 cointegrating relations.

**Table 2: Johansen Cointegration test**

On the basis of the VAR framework, we conduct the Granger Causality test to capture the lead-lag relationship between freight rates and crude steel production. Table 3 summarizes the test results.

The results suggest that for the Capesize, there is significant causality from Chinese steel production to freight rates in the spot market and less significant in the period (10% level). In fact, a bi-directional relationship exists between China's steel production and Capesize rates. A similar two-way lead-lag relationship is generated in the Supramax sector as well. However, for the Panamax, the Chinese steel production leads both the spot and period freight rates, but the opposite is not true. As for the Handysize, there is a bi-directional lead lag relationship in the period market and a unidirectional in the spot (Chinese steel production causes average trip rates).

| Vessel size | Dependendent variable | Excluded variable | Lags | Chi-sq. (p-value) | Outcome | Residual Serial Corr. LM test | Residual Heteroskedasticity | R-sq. |
|---|---|---|---|---|---|---|---|---|
| Capesize | avg spot | Ch_steel_pr | 3 | 0.0105** | causality at 5% | 0.9696 | 0.0000*** | 0.845481 |
| | Ch_steel_pr | avg spot | 3 | 0.0628* | causality at 10% | | | |
| | 6-m tc 170k | Ch_steel_pr | 2 | 0.0592* | causality at 10% | 0.3098 | 0.1194 | 0.917079 |
| | Ch_steel_pr | 6-m tc 170k | 2 | 0.0226** | causality at 5% | | | |
| Panamax | avg spot | Ch_steel_pr | 3 | 0.0001*** | causality at 1% | 0.3096 | 0.0000*** | 0.911647 |
| | Ch_steel_pr | avg spot | 3 | 0.2578 | no causality | | | |
| | 6-m tc 75k | Ch_steel_pr | 3 | 0.0563* | causality at 10% | 0.7607 | 0.0609* | 0.950389 |
| | Ch_steel_pr | 6-m tc 75k | 3 | 0.1012 | no causality | | | |
| Supramax | avg trip | Ch_steel_pr | 3 | 0.0000*** | causality at 1% | 0.8926 | 0.0000*** | 0.932998 |
| | Ch_steel_pr | avg trip | 3 | 0.0004*** | causality at 1% | | | |
| | 6-m tc 52k | Ch_steel_pr | 3 | 0.0085* | causality at 1% | 0.9921 | 0.0074*** | 0.948135 |
| | Ch_steel_pr | 6-m tc 52k | 3 | 0.0041* | causality at 1% | | | |
| Handysize | avg trip | Ch_steel_pr | 2 | 0.0156* | causality at 1% | 0.0557 | 0.0945* | 0.785554 |
| | Ch_steel_pr | avg trip | 2 | 0.4091 | no causality | | | |
| | 6-m tc 30k | Ch_steel_pr | 3 | 0.0497 | causality at 5% | 0.6074 | 0.0006*** | 0.966965 |
| | Ch_steel_pr | 6-m tc 30k | 3 | 0.0004* | causality at 1% | | | |

*Notes:*
*** indicates rejection of Ho at 1% level, **at 5% and * at 10%
Ho: All lagged terms of excluded variable insignificant
The test statistic follows the chi-square distribution under Ho
VAR Residual Heteroskedasticity Tests: No Cross Terms / Ho: homoscedasticity in residuals
VAR Residual Serial Correlation LM test / Ho: no serial correlation at lag order h

**Table 3: Granger Causality Test**

Finally, the results reported in Table 3 show that our model is acceptable in terms of goodness of fit and residual diagnostics.

The last step of our methodology involves Impulse Response analysis. The results are provided in figures 1.1-1.16 respectively. The horizontal axis represents the number of months after the shock, while the vertical axis measures the magnitude of the effect on the variables.

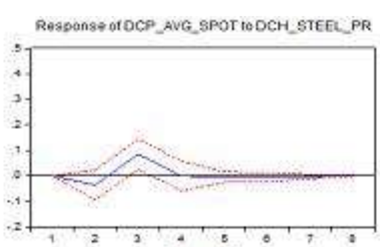


Figure 1.1

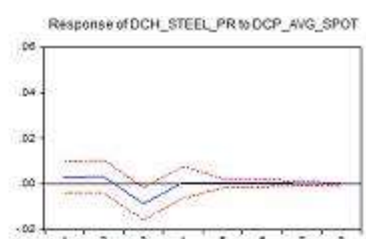


Figure 1.2

In Figure 1.1 it is observed that a positive shock to steel output, initially triggers a negative reaction of the spot market, which can be attributed to market nervousness, as the Capesize spot market is highly dependent on Chinese iron ore imports and a high output may create worries of overcapacity. However, the high level of steel production creates the need to restock the raw materials utilized in the steel mills, and usually this process starts taking place one month later. This explains the positive response of the Capesize spot market after approximately 1.5 month, as the graph shows. At some point the restocking phase ends, leading to a decline in the demand for transport and consequently Capesize spot rates. Eventually, the effects of the shock die out, as no co-integration relationship exists.

Figure 1.2 illustrates that for the first 1-1.5 month the steel plant's reaction to a positive shock on Capesize freight rates is relatively neutral, as the high output does not create the need for immediate restocking. However, the stockpiles at some point need replenishment, but the high freight rates add up to the production cost and lead to the decision to lower the steel production until the freight rates are adjusted downwards and then scale it up. This process is depicted in Figure 1.2, where the response is steady, then negative and then positive until it abates.

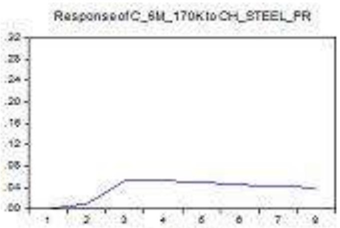


Figure 1.3

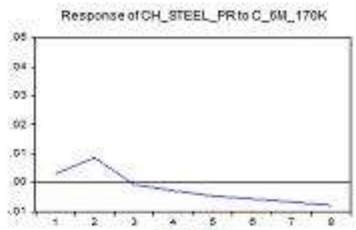


Figure 1.4

Looking at the period Capesize market, in Figure 1.3, it is noticeable that the period rates, contrary to the spot, are not negatively affected over the first 1-1.5 month, but they rather remain relatively steady. This is reasonable, since the t/c rates are not so much affected by the sentiment concerning the current state of the market, but mainly by the expectations of its future direction. Following that, the period rates start to increase, corresponding to the expectation of a new seasonal increase in production and imports of raw materials. In this case, after some overshooting, the rates and the steel production reach a long term equilibrium stemming from their co-integration.

The steel response is different in the case of a positive shock to period rates. A rise of a 6-month time charter actually implies that the expectation is that there is a positive freight market expectation for the next 6 month period. From the point of view of the steel plants, since they prefer low transport costs, this is alarming and leads them to import more and increase their stockpiles in view of a likely future upswing in transport costs. Therefore, the raw materials imports spur a short term growth in the steel production, as Figure 1.4 depicts, which is followed by a longer term and continuous limitation of production due to the high freight rates, until the level of production reaches its equilibrium level (coming from co-integration).

The rest of the graphs can be found in the Appendix. It is worth noting that in all other sizes the respective responses fluctuate in a similar manner.

The main difference is that in smaller vessel sizes (Handysize and Supramax), as the vertical axis displays, the magnitude of the effect on their freight rates is much lower than in the larger categories (Panamax and especially Capesize). In fact, the results reveal that the magnitude of the effects on larger vessel freight rates can be twice as high, in maximum value terms. This is a consequence of the higher dependence of the larger types on the iron ore trade, as it constitutes their main cargo (together with coal for Capezizes and coal and grain for Panamaxes). On the other hand, the smaller Handysize and Supramax are more versatile, as they target a variety of cargoes, including minor bulks. Therefore, this characteristic makes them less dependent on iron ore trade and in turn less influenced by a shock in steel production.

## 5. Conclusions

This paper investigates the interactions between Chinese steel production and dry bulk freight rates. The study contributes to the literature by examining this relationship using causality analysis. Our analysis focuses on four different vessel types, in the context of both the spot and the period freight market.

The empirical results support the existence of a causal relationship between China's steel production and freight rates, which is unidirectional for Panamax and the spot market of Handyzise, and bi-directional in all other segments.

Furthermore, the Impulse Response analyses identifies the responsiveness of the dependent variables to a positive shock and indicates that freight rates of larger vessels are more affected by a change in steel production.

At the practical level, our study contributes to the better understanding of the relationship between freight rates and Chinese steel production, and can improve operational management and budget planning decisions.

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## Appendix

### Panamax

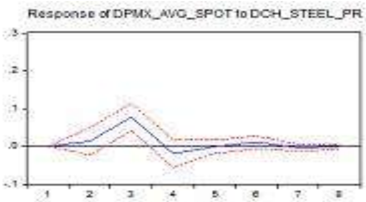



Figure 1.5

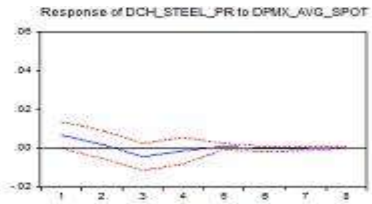
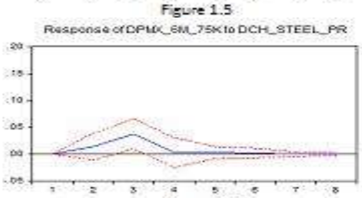



Figure 1.6

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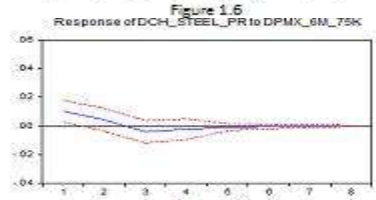


Figure 1.8

### Supramax

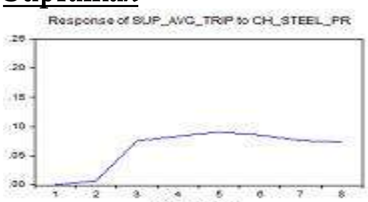


Figure 1.9


Figure 1.10

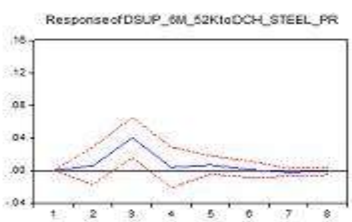


Figure 1.11

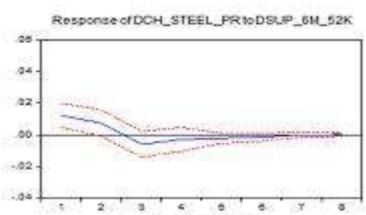


Figure 1.12

### Handysize

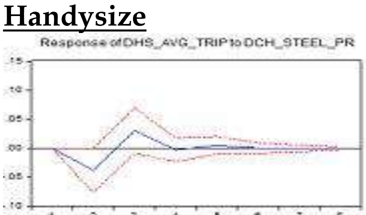


Figure 1.13

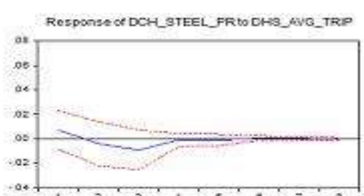


Figure 1.14

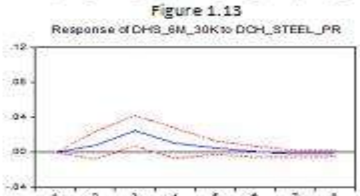


Figure 1.15

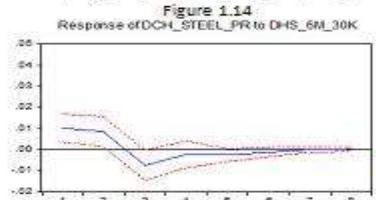


Figure 1.16