



DYNAMIC ECONOMIC RELATIONS AMONG STEEL PRICE INDICES

Ming-Tao Chou

Department of Aviation and Maritime Management, Chang Jung Christian University, Tainan, Taiwan, R.O.C.,
mtchou@gmail.com

Follow this and additional works at: <https://jmstt.ntou.edu.tw/journal>



Part of the [Engineering Commons](#)

Recommended Citation

Chou, Ming-Tao (2016) "DYNAMIC ECONOMIC RELATIONS AMONG STEEL PRICE INDICES," *Journal of Marine Science and Technology*. Vol. 24 : Iss. 5 , Article 3.

DOI: 10.6119/JMST-016-0504-1

Available at: <https://jmstt.ntou.edu.tw/journal/vol24/iss5/3>

This Research Article is brought to you for free and open access by Journal of Marine Science and Technology. It has been accepted for inclusion in Journal of Marine Science and Technology by an authorized editor of Journal of Marine Science and Technology.

DYNAMIC ECONOMIC RELATIONS AMONG STEEL PRICE INDICES

Ming-Tao Chou

Key words: bulk shipping companies, steel price index, vector autoregressive moving-average model.

ABSTRACT

Bulk shipping is now a globalized industry, with market prices entirely dependent on the world's economic climate. For the bulk shipping market, the steel price index is a crucial standard of reference. In a global industry, the ability to understand the international relationship between changes in information and their effects on economics can help to reduce losses caused by the uncertainty of risk. Because the types of ships and contracts used in bulk shipping are wide-ranging, market participants tend to have difficulty in determining market price changes and trends, and are therefore forced to face greater market uncertainty and volatility. Because steel price is one of the leading indicators used in the bulk shipping market, a clear understanding of steel price index fluctuations can help to reduce the risks associated with bulk shipping. This study uses the vector autoregressive moving-average model as the principle method of analysis to determine how three major economic variables representative of Asian Steel Price Index (ASI), European Steel Price Index (ESI), and North American Steel Price Index (NASI) might influence one another. The results are as follows: (1) ASI is affected by its own positive changes as well as those of NASI, whereas the ESI is only affected by its own moving average. (2) The ASI and NASI are considered as leading indicators. This study aims to provide bulk shipping participants with additional ideas to determine the ideal time to enter the market.

I. INTRODUCTION

As a raw material, steel plays a pivotal role in the world economy, with the steel price index reflecting market prices on the basis of supply and demand. The index is one of the leading indicators used in the bulk shipping industry (Chou and Lin, 2010). The iron price index (IPI) commonly used in

the bulk shipping industry is the world IPI, which is part of the balanced index category associated with global steel transactions. The Global Steel Price Index is divided based on region into three types: Asian Steel Price Index (ASI), European Steel Price Index (ESI), and North American Steel Price Index (NASI). Together, these three indices form the Global Steel Price Index. In the global shipping market, the steel price index mainly affects international bulk shipping market prices because cargo ships are mostly irregular bulk ships. Thus, steel price index fluctuations have a direct influence on bareboat voyage charter and time charter leases for bulk shipping (UNCTAD, 2009-2015). The bulk shipping market is almost perfectly competitive, where the price of supply and demand is often closely linked to the world economy (Kavussanos, 1996), and where the steel price index is also closely associated with the shipping market. Therefore, regardless of their professions as an operator or a manager in the maritime industry, those who can understand the relative relationships among various factors affecting the maritime market can help to reduce risks and increase profitability. As such, the ability to successfully predict future trends in this business can substantially help to avert risk (Cullinane, 1995; Hsieh et al., 2013; Nicolás, 2015). For bulk shipping operators, a thorough understanding of cyclic variations in the steel price index can help to improve the quality of dynamic bulk shipping market information, which can effectively reduce the risks managed by the company.

According to the Barry Rogliano Salles (Barry Rogliano Salles, 2009) and the United Nations Conference on Trade and Development (UNCTAD) reports, because of the gradual recovery of the world economy since 2003, along with the demand created by the Olympic Games hosted by China and the 2010 Shanghai World Expo, there has been an urgent demand from China for raw materials, which has indirectly strengthened international shipping needs (Chou and Lin, 2010; Chou and Huang, 2010; Chou et al., 2012). Currently, in terms of the total iron ore import in Asia, China's total import accounts for more than half (UNCTAD, 2009-2015). However, regular shipping and bulk shipping have not been able to provide enough ships in a timely manner for the transport of materials, thus leading to a massive increase in international shipping costs. The 2008 BRS report showed that by the end of June 2006, the unwillingness of Australian and Brazilian ore exporters to accept ships that were more than 25 years old, coupled with

BHP's (BHP is a mining company) one-month ore export port renovation, had resulted in the substantial tightening of the transport capacity of Capesize vessels. This further led to the rapid rise of the Baltic Capesize Index (BCI), the effects of which affected the Baltic Dry Index (BDI), which also showed the phenomenon of a rapid rise. At the time, regardless of the purpose of their use, be it a time charter or a voyage charter, leases were all increasing in cost, with the daily time charter rental cost of Capesize vessels reaching the sky-high price of USD 1,762 (UNCTAD, 2009). Even 2015, the time charter rate of Capesize reaches its historical lowest level, its daily rent rate remains hold at the level of US \$6,000. With the increase in leasing costs, bulk shipping professional managers began to use derivative financial instruments as hedging tools. Hedging instruments traditionally used in bulk shipping as a reference for hedging standards include the steel price index and the BDI (Chou and Lin, 2010; Chou and Huang, 2010; Chou et al., 2012; Chou et al., 2015), which are considered as the most crucial reference indices by the bulk shipping industry. The BDI can show the current rental situation in the bulk shipping market, whereas the steel price index is the main index for bulk raw materials. They are crucial indicators that reflect the economic climate, with the steel price index showing the bulk market situation ahead of the BDI by approximately six months (Chou and Lin, 2010). This allows an understanding of the importance of the steel price index to the bulk shipping industry.

As the 2008-2009 financial crisis swept across the world (Allen and Snyder, 2009; Keys et al., 2010), the bulk shipping industry clearly did not escape its effects. To increase the understanding of bulk market risks, the steel price index, as opposed to the BDI, has been set as the leading indicator (Chou and Huang, 2010; Chou and Lin, 2010; Chou et al., 2012; Chou et al., 2015). This study analyzes steel price index dynamics to obtain data that would be useful to bulk shipping industry operators and managers. This study uses the ASI, ESI, and NASI as the main cost variables, with each index series adjusted based on steadiness. It also uses the vector autoregressive moving-average (VARMA) model to verify the leading and lagging periods within Series ASI, ESI, and NASI, so that the direct leading and lagging rules applied to the steel price series from these three areas, as well as their dynamic relationships, can be understood.

II. LITERATURE REVIEW

The BDI was relatively stable from June 2000 to 2002, fluctuating slightly by approximately 2,000 points (The Baltic Exchange, 2015). According to the study by Ekawan et al. (2006), steel production since 1950 has gradually relocated from Europe and America to Asia. With China being the major importing country, the average annual growth rate during 1998-2007 was 5% (The Baltic Exchange, 2015; UNCTAD, 2009-2015). In terms of iron ore, Brazil and Australia are the major exporting countries, whereas Asia is the main importing area, especially

with China as a crucial importing country in this region (Chou and Huang, 2010; Chou and Lin, 2010; Chou et al., 2012; Chou et al., 2015; The Baltic Exchange, 2015). The main reason for this is the short travel distance between Australia and China. According to statistics from BRS (2009), from 2000 to 2002, Brazil Tubarao set its ore freight rate to the Far East at USD 3-9 per ton, whereas the 2008 cost per ton from Australia to China was USD 45; from Brazil to China, the cost was USD 107. With regard to location and the average cost, China preferred to import iron ore from Australia (UNCTAD, 2009-2015). Since 2003, among all shipping-related industries, bulk shipping has undergone the most substantial changes in shipping costs. By the end of June 2006, the refusal of Australian and Brazilian ore exporters to accept ships that were more than 25 years old and waiting to be phased out, coupled with BHP's one-month ore export port renovation, had resulted in the tightening of the transport capacity of Capesize vessels (BRS, 2009). By 2007, the BDI had reached its peak of 11,000 points. During the first quarter of 2007, signs of thievery of raw materials began to appear. At present, Capesize vessels are used as the primary iron ore transport equipment (Alizadeh and Nomikos, 2002). As a result of rapid global economic development, increasing raw material prices, inflation, the strong demand for shipping capacity, and the demand for other factors, the global iron ore price negotiation of 2007 entered its most critical final period. The international steel price index also reached its historically highest value of 282 in the third quarter of 2008. Subsequently, the financial crisis swept across the world, resulting in the plunge of the international steel price index in the fourth quarter of 2008 by 31.8% to 192.8; the index remained at approximately 220 in 2012. The international steel price index is one of the reference indices used by shipping and mining companies (Chou et al., 2015). As the transparency of information increases, relevant capital investments will be attracted to this market, thus leading to the increasing transparency of the international steel price index.

In 2002, the origins of a turnaround in the shipping industry became perceptible following the increase in demand for coal and iron due to the growth of China and other emerging countries. Astier (2001) asserted that because of the urgent demand for raw material imports, mainly iron ore and coal, from developing countries as a result of economic development, the international steel price index from 2002 to the third quarter of 2008 increased by as much as 300%. Currently, China is Asia's largest importing country, accounting for approximately 444 million tons in 2008, which was an increase of 61 million tons from that in 2007 (UNCTAD, 2009-2015). Brazil and Australia are the two major iron ore exporters. Clarkson Research Studies (2008) mentioned that China accounts for more than half of the global coal imports. Because the transport time between Australia and China is short, China is currently more likely to import iron ore from Australia (UNCTAD, 2009-2015). Capesize-type ships are major transport vessels used to carry iron ore and coal. Table 1 shows that the current tonnage for the three shipping routes is 150,000 MT, all denominated in

Table 1. Forward freight agreement trading pattern.

Route	Ship type	Actual trade route	Tonnage	Trading unit
C4	Capesize	Richard Bay/Rotterdam	150,000 MT	1,000 MT
C7	Capesize	Bolivar/Rotterdam	150,000 MT	1,000 MT
BCI 4TC	Capesize	Combination route (C8: Gibraltar/Hamburg trans atlantic round voyage, C9: Continent/Mediterranean trip China-Japan, C10: China-Japan trans pacific round voyage, C11: China-Brazil round voyage)	180,000 MT	In-days

Source: The Baltic Exchange (2015).

US dollars. Because shipping routes other than BCI 4TC, which uses in-days, use 1,000 MT as the trading unit, the ASI increased, reaching its highest historical point in 2008.

In terms of futures and forward prices, Kavussanos and Nomikos (1999) believed in the relatively stronger predictive power of futures price. Therefore, this study considers the international steel price index as a major index. In terms of risk, the cost of additional expenses for short-term market investors is comparably low; however, in the long term, because error in forecast will increase, an increase in risk will follow (Alizadeh and Nomikos, 2003). Different types of ships can have different characteristics associated with the changes in risk and time. At present, ships that carry steel are mostly of the Capesize type, and the six-month lead of the steel price index ahead of the BDI allows bulk market conditions to be shown first (Chou and Huang, 2010; Chou and Lin, 2010; Chou et al., 2012; Chou et al., 2015). Therefore, in terms of the business of running an international bulk shipping company, the steel price index can be regarded as the main reference index. Through in-depth analysis, this study obtains results that not only theoretically verify the dynamic economic aspects of the steel price index but also provide practical assistance to bulk shipping companies in practical decision-making.

III. METHODOLOGY

It has been more than 20 years since univariate time series models and multivariate time series models have been employed as research methods. Hansen and West (2002) regarded multivariate time series models as a crucial method of macroeconomic time series research in the past 25 years. Multivariate time series demonstrate both the function of describing changes in macroeconomic time series as well as the structural causality within a macroeconomic time series (Stock and Watson, 2001). These two functions are also the main reasons why this macroeconomic model has been used often. When conducting research analysis, it may be necessary to consider not only the influence of each individual variable but also the influence of multiple variables, including the causality relationships among them. Causality includes the leading or lagging relationships of variables; as a result, the majority of studies on causality have chosen to use the VARMA model (Chou and Huang, 2010; Chou and Lin, 2010; Chou, 2011; Chou et al., 2015). However, the time series studies conducted with regard to the shipping industry have only focused on single indices in

terms of their historical data and forecasting ability. However, with regard to the IPI, its movement trends may vary according to social and economic situations. Furthermore, because this study examines the relationships among the IPI sub-indices for the various IPI regions, it would not be appropriate to use a traditional autoregressive integrated moving-average model because such a model cannot identify the relationships among the variables (Kavussanos and Visvikis, 2006). In other words, changes in the IPI reflect a type of dynamically volatile index. We must thoroughly study its characteristics to achieve useful forecasts. The VARMA model can effectively construct dynamic relationships among the variables and improve forecasting accuracy (Hamilton, 1994). Prior to building a VARMA model, we must conduct a unit root test on the ASI, ESI, and NASI to determine their status. Otherwise, we would only be able to examine whether co-integration exists among these sub-indices.

We extract k series from equal time such as IPI_A , IPI_E , and IPI_{NA} , as follows:

$$\{IPI_{1t}\}, \dots, \{IPI_{kt}\}, t = 0, \pm 1, \pm 2, \dots$$

Alternatively, this can be demonstrated using vectors:

$$\underline{IPI}_t = [IPI_{1t}, \dots, IPI_{kt}]'$$

Subsequently, we call this k series as a time series with a k degree of vector.

Generally, a univariate IPI is assumed to be IPI_t , which has an ARMA(p, q) model (Tiao and Tsay, 1983) with a stochastic difference equation as follows:

$$\phi_p(B)IPI_t = C + \theta_q(B)a_t$$

In the above equation, B is a backward shift operator.

$\phi_1, \phi_2, \dots, \phi_p$ is called an autoregression parameter.

$\theta_1, \theta_2, \dots, \theta_q$ is called a moving average parameter.

C is the constant.

The VARMA model of the IPI can be rewritten using a matrix, as follows:

$$\underline{\phi}(B)\underline{IPI}_t = \underline{\theta}(B)\underline{a}_t$$

where B is the matrix polynomial of the latter operation, $\underline{\phi}$ and $\underline{\theta}$ are a k by k matrix, \underline{C} is k by a one constant value vector, and a_t is a series of independent normal distributed stochastic volatility vectors with zero as the average value. Its covariance matrix is Σ , and its constant vector is \underline{C} , which can be demonstrated as constant C as follows:

$$\underline{C} = (\underline{I} - \underline{\phi}_1 - \underline{\phi}_2 \cdots - \underline{\phi}_p) \underline{\mu}$$

Conducting a unit root test requires us to assume that the roots of the polynomial determinants $|\underline{\phi}(B)|$ and $|\underline{\theta}(B)|$ are outside of the unit circle. If the roots of $|\underline{\phi}(B)|$ are outside the unit circle, then \underline{IPI}_t is stable. On the contrary, if the roots of $|\underline{\theta}(B)|$ are outside the unit circle, then \underline{IPI}_t is reversible.

For the IPI sub-index that is nonstationary, assuming this is because its average value is not constant, we must convert the series into a stationary one by applying a finite difference method. By contrast, if the reason that it is nonstationary is because its covariance is not constant, then we can adopt a method of transition function. Generally, by extracting the natural logarithm of a data series, we can convert its covariance into a constant. In this study, we calculate the logarithm of the series before conducting further analysis.

If we assume the final IPI model to be VARMA (1, 1), then $\underline{\phi}(B)\underline{IPI}_t = \underline{C} + \underline{\theta}(B)a_t$ can be simplified as follows:

$$\underline{I} - \underline{\phi}(B)\underline{IPI}_t = (\underline{I} - \underline{\theta}B)a_t$$

All the elements of its matrix and vectors are as follows:

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} - \begin{pmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ \phi_{21} & \phi_{22} & \phi_{23} \\ \phi_{31} & \phi_{32} & \phi_{33} \end{pmatrix} B \begin{bmatrix} ASI_{1t} \\ ESI_{2t} \\ NASI_{3t} \end{bmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} - \begin{pmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \\ \theta_{31} & \theta_{32} & \theta_{33} \end{pmatrix} B \begin{bmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \end{bmatrix}$$

The parameters of the equation above ϕ_{ij} and θ_{ij} demonstrate how the i series are affected by the j series. Simultaneously, this matrix can also be used as the principle equation of this study, through which we can determine relationships among the IPI's subindices.

To determine the autoregressive characteristics of the IPI, our study employs the partial autoregression matrix proposed by Tiao and Box (1983), and the extended cross-correlation matrix methods proposed by Liu et al. (2004-2005). Furthermore, on the basis of the aforementioned methods, we can undertake a smallest canonical correlation analysis (SCAN) to create a mixed VARMA model for a vector time series. SCAN is not only able to identify which model to use but also can identify the order of the VARMA. When selecting the appropriate models to use in any time series analysis, we commonly apply

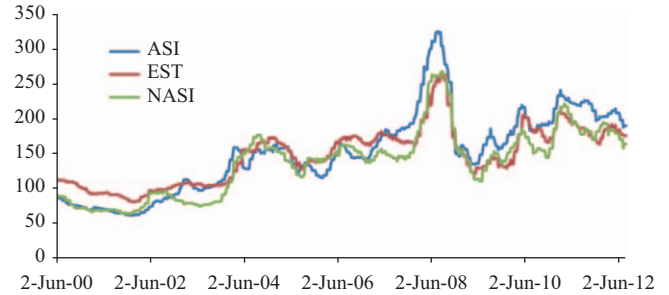


Fig. 1. Diagram of the ASI, ESI, and NASI trends.

Akaike's Information Criterion or Schwartz's Bayesian Criterion Schwartz's as model selection references (Akaike, 1973; Schwarz, 1978). The judging standard of these two criteria is that a smaller value represents a more favorable performance of the model (Hamilton, 1994; Liu et al., 2004; Liu et al., 2005).

IV. EMPIRICAL ANALYSIS

This study uses the ASI, ESI, and NASI from June 2, 2000 to July 27, 2012 as series variables, with 635 pieces of cyclical data per series. The ASI on June 5, 2008, the ESI on May 19, 2008, and the NASI on May 22, 2008 were at their historical highs of 19,687, 11,345, and 6,743, respectively. When indices that have reached high points are subjected to the shock of a financial crisis, they can experience an enormous drop, as shown in Fig. 1. If the dropped values are further compared to the ten-year average and variance values, the index drop becomes highly perceptible. After the 2008 bull market, the indices have now returned back to their fundamental levels.

The ASI, ESI, and NASI trend diagrams in Fig. 1 show an average value of 152.52 at a standard deviation of 58.37 for the ASI, 148.95 at 40.10 for the ESI, and 139.18 at 47.87 for the NASI. Fig. 1 shows that the trends were moving upward for the ASI, ESI, and NASI before 2008; they then reached historical highs of 325.97 on July 25, 2008 for the ASI, and 264.14 on August 22, 2008 for the ESI and NASI. After the financial tsunami, the ASI, ESI, and NASI dropped to the bottom of the wave band in May 2009 before stabilizing over time as the economy began to recover. The IPI was again affected by the financial tsunami and reached the bottom of the band in February 2009; by contrast, the ASI, ESI, and NASI began to move upward again and remained stable over time as the economy began to recover.

Overall, economic variables are mostly nonstationary series (Nelson and Plosser, 1982), and the ASI, ESI, and NASI series analyzed in this study are only some of the overall economic variables. Before conducting the VARMA estimation, this study performs a unit root test on each variable to verify that the series are in stable conditions. After passing the unit root test, the series undergo the causality test; otherwise, only co-integration between the variables would be verified (Engle and Granger, 1987). To smooth out the ASI, ESI, and NASI

Table 2. Unit root test on the original series.

	ASI	ESI	NASI
with Constant and trend	-4.32*	-4.08*	-3.98*

Note: The significance level of the ADF test threshold value at 1% (*), 5% (**), and 10% (***) are -3.97, -3.42, and -3.13, respectively.

series and to reduce forecast errors, this study takes the logarithm of the original data and compresses its extreme data values to facilitate subsequent analyses. The study first takes the natural logarithm of the original series before performing the steady-state analysis. The test results are shown in Table 2. In this table, the results show a significance level under 5%, indicating that the ASI, ESI, and NASI series are steady-state series.

After SCAN graphics verification (Table 3), according to the exact model, the optimal VARMA model for the ASI, ESI, and NASI series should be VARMA (3, 1). Because the estimated model at the third-order parameter for the MA section is not significant, this study uses VARMA (2, 1) as the optimal model for analysis (Liu et al., 2004; Liu et al., 2005), which is consistent with the simple model requirements proposed by

Table 3. Results of SCAN.

Q:	0	1	2	3	4	5	6
0:	X	X	X	X	X	X	X
1:	X	0	0	X	X	0	0
2:	0	0	0	X	0	0	0
3:	X	0	0	0	0	0	0
4:	X	0	0	0	0	0	0
5:	X	0	0	0	0	0	0
6:	0	0	0	0	0	0	0

Lütkepohl (1985).

The accuracy of the likelihood estimation of the original VARMA (2, 1) model is adjusted so that insignificant variables within the equation are removed, which further streamlines the model for improved estimation efficiency. The VARMA (2, 1) model is the ideal model for the ASI, ESI, and NASI because it demonstrates the existence of a two-period lagging phenomenon among the ASI, ESI, and NASI, as well as an error correction factor. The resulting coefficients are shown in the following matrix.

$$\begin{bmatrix} ASI \\ ESI \\ NASI \end{bmatrix}_t = \begin{bmatrix} 0.509 \\ (0.784) \\ 149.091 \\ (1.634) \\ 2.004 \\ (0.826) \end{bmatrix} + \begin{bmatrix} 0.884 & 0 & 0.652 \\ (0.039) & (---) & (0.061) \\ 0 & 0 & 0 \\ (---) & (---) & (---) \\ 1.311 & 0 & 0.976 \\ (0.120) & (---) & (0.013) \end{bmatrix} \begin{bmatrix} ASI_{t-1} \\ ESI_{t-1} \\ NASI_{t-1} \end{bmatrix} + \begin{bmatrix} 0.112 & 0 & -0.652 \\ (0.042) & (---) & (0.055) \\ 0 & 0 & 0 \\ (---) & (---) & (---) \\ -1.303 & 0 & 0 \\ (0.121) & (---) & (---) \end{bmatrix} \begin{bmatrix} ASI_{t-2} \\ ESI_{t-2} \\ NASI_{t-2} \end{bmatrix} + \begin{bmatrix} -0.144 & 0 & 0.643 \\ (0.046) & (---) & (0.052) \\ 0 & -0.940 & 0 \\ (---) & (0.012) & (---) \\ 1.235 & 0 & 0 \\ (0.122) & (---) & (---) \end{bmatrix} \begin{bmatrix} a_{ASI_{t-1}} \\ a_{ESI_{t-1}} \\ a_{NASI_{t-1}} \end{bmatrix}$$

Because matrix patterns cannot easily show the relationships among variables, the matrix pattern is expanded as follows:

$$ASI_t = 0.509 + 0.884_{ASI_{t-1}} + 0.652_{NASI_{t-1}} + 0.112_{ASI_{t-2}} - 0.652_{NASI_{t-2}} - 0.144_{a_{ASI_{t-1}}} + 0.643_{a_{NASI_{t-1}}}$$

$$ESI_t = 149.091 - 0.940_{a_{ESI_{t-1}}}$$

$$NASI_t = 2.004 + 1.311_{ASI_{t-1}} + 0.976_{NASI_{t-1}} - 1.303_{ASI_{t-2}} + 1.235_{a_{ASI_{t-1}}}$$

This equation clearly shows the relationships among the ASI, ESI, and NASI series, with the ASI being positively affected by itself and by the NASI, whereas the ESI is only affected by its own moving average (Granger, 1969). This equation shows that the ASI of the current period is positively affected by its own data from the previous period as well as by the data of the NASI from the previous period. The ASI changes because of the lag resulting from the positive effect of two of its own previous periods as well as the negative effect

of two of the NASI periods. The NASI of the current period is positively affected by its own data from the previous period and by the data of the ASI from the previous period; it is negatively affected by the multiplier effect from the ASI because of its lag of two periods. Empirical evidence in the study shows that the ASI and NASI are mutually reinforcing indices with effects that exceed that of the ESI.

The ASI, ESI, and NASI trends from 2000 to 2012, as well as the results of this study, show the following:

1. The relationships among the ASI, ESI, and NASI are steady-state series that match the assumptions of time series analysis.
2. The ASI, ESI, and NASI are indices created to reflect the three major steel-producing regions in the world, with the ASI and NASI having a mutually reinforcing relationship of the bidirectional series type, whereas the ESI tends to decouple from the ASI and NASI. This suggests that the steel industry in the European market is close to saturation.
3. The ASI and NASI are leading steel price indices. Thus, for

investors or shipping companies, an interpretation of the freight rate by using the suggested ASI can be further assisted with the use of the NASI.

V. CONCLUSION AND SUGGESTIONS

1. Conclusion

This study used the VARMA model to deconstruct the causal relationships among the ASI, ESI, and NASI. The results obtained can be used to interpret and explain the freight rates charged by shipping companies or related industries. The ultimate use of the model is in the estimation of future freight rates. Overall, under the study's assumptions, the ASI, ESI, and NASI results show that the ASI and NASI are leading indices. The main conclusions of this study include the following:

1. The VARMA model's adjusted estimation results show that the ASI is positively affected by itself and the NASI series, whereas the ESI is only affected by its own moving average.
2. The VARMA theory shows that the ASI and NASI are leading indicators. This finding suggests that the ASI and NASI should be used by investors or shipping companies for interpretations or predictions. The results from this study may enable investors and relevant companies to increase their understanding of the relative relationship between the ASI and NASI. When the steel market is under the influence of seasonal fluctuations or negative economic conditions, the ASI and NASI can be used to forecast the rising market's freight rate so that investment strategies to minimize risks for shipping companies can be formulated.

2. Implications for Management

The management implications of this model derive from the dynamic effects of the ASI, ESI, and NASI, with the ASI and NASI being the major steel price-deciding indices at present. The pattern of their matrix can be used to understand the mutual reinforcing relationship variables between the ASI and NASI, with the ESI affected only by its own moving average. This result adequately corresponds to the existing steel production pattern and method. This section of the paper shows the main influencing coefficient factors affecting the ASI, ESI, and NASI, one of which is related to Asia being the most frequent steel-trading region (Chou and Lin, 2010). Because steel production and manufacturing require high energy consumption and pollution, the matrix equation can be used to compare the ESI between current market situations in Europe and other regions to determine their relative weaknesses. Current European regulations on greenhouse gas emissions are relatively stricter than those in Asia and America (Koop and Tole, 2013); because this is relatively unfavorable for the European steel production industry, it is relatively favorable for Asia, the region that is currently experiencing strong growth and demand. Hence, the effect of the advanced indication of conditions by the steel price index in these two regions is apparent. Because

developed countries and developing countries are located in different regions with different requirements for raw materials, coupled with the reallocation of the steel production region after 1950, steel production has decreased in Europe and America (Ekawan et al., 2006). Since 2003, China has become one of the largest iron ore importing countries (Clarkson, 2008). Considering this and the active infrastructure construction in Asia, the meaning of the matrix equation is evident.

3. Research Limitations and Recommendations

Regardless of theory or practice, the use of the ASI, ESI, and NASI as shipping industry indices to interpret shipping costs warrants research. As discussed previously, under appropriate assumptions, the VARMA can be used for simulation purposes: It can obtain the ASI, ESI, and NASI for use as reference price values for shipping companies. However, this study had several limitations; the difficulties and limitations and their solutions are summarized as follows:

1. Actual shipping costs are not limited to the ASI, ESI, and NASI; the ASI, ESI, and NASI used in this study are only three of the many indices that shipping companies can use as reference. There are also other relevant factors that might affect freight cost, such as oil price, shipping company alliances, and economic crises. Major companies in the shipping industry adopt dynamic shipping pricing strategies. Other shipping companies may also influence each other. Regardless of whether the shipping cost is set too high or too low, these factors all lead to changes in the profits of shipping companies.
2. The data type used in this study for corresponding analysis and estimations is cyclical. Because the VARMA model does not take seasonal influences into account, to overcome this problem, seasonal variations can be added to enhance the accuracy and validity of the VARMA model.
3. The literature on the current ASI, ESI, and NASI database remains scarce. We suggest the involvement of relevant scholars and experts in this type of research to enhance the basis for future applications.
4. This study only used three indices as research subjects to estimate the causal relationships among them. Future research should include various other indices in dynamic assessments so that different influencing indices would be involved, and common general principles could be determined as a result of such investigations.

Investors and regular shipping companies can use the results obtained from this study by using the ASI and NASI to predict the increase of future freight rates when the regular shipping market is influenced by factors such as seasonal fluctuations or a poor economy. By making informed predictions, investors and shipping companies can develop more effective investment strategies, thereby averting the potential risks associated with shipping companies.

ACKNOWLEDGEMENT

The authors are grateful for the financial sponsorship of the Ministry of Science and Technology (project number 100-2410-H-309-001).

REFERENCE

- Alizadeh, A. H. and N. K. Nomikos (2002). The dry bulk shipping market, In Grammeons, C. Th. (Eds.), *The Handbook of Maritime Economics and Business*, London: Loyd's of London Press Ltd.
- Alizadeh, A. H. and N. K. Nomikos (2003). The price-volume relationship in the sale and purchase market for dry bulk vessels. *Maritime Policy and Management* 30, 321-337.
- Allen, R. E. and D. Snyder (2009). New thinking on the financial crisis. *Critical Perspectives on International Business* 5, 36-55.
- Astier, J. E. (2001). The evolution of the world iron ore market. *Mineral and Energy* 16, 23-30.
- Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle, In B. Petrov and F. Csake, eds., *Second International Symposium on Information Theory*.
- Barry Roglian Salles. (2009). The dry bulk market in 2008. *Shipping and Shipbuilding Market*, 24-31.
- Chou, M.-T. and B.-C. Huang (2010). An analysis of the relationship between forward freight agreements and steel price index - An application of the vector ARMA model. *African Journal of Business Management* 4, 1149-1154.
- Chou, M.-T. and S.-C. Lin (2010). An analysis of the relationships between baltic dry index and steel price index- An application of the vector AR model. *Journal of the Chinese Institute of Transportation* 22, 211-232.
- Chou, M.-T., Y.-L. Yang and S.-C. Chang (2012). A study of the dynamic relationship between crude oil price and the steel price index. *Review of Economics and Finance* 5, 30-42.
- Chou, M. T., Y.-L. Su, T.-U. Chou and H.-U. Lian (2015). An analysis of the relationship between Asian steel index and the baltic capsize index. *Modern Economy* 6, 207-216.
- Cullinane, K. (1995). A portfolio analysis of market investments in dry bulk shipping. *Transportation Research Part B* 19, 181-200.
- Clarkson Research Studies. (2008). *Dry bulk trade outlook*, Clarkson Research Service Limited 14, 1-28.
- Ekawan, R., M. Duchene and D. Goetz (2006). The evolution of hard coal trade in the pacific market. *Energy Policy* 34, 1853-1866.
- Engle, F. and C. W. J. Granger (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica* 55, 251-276.
- Hansen, B. E. and K. D. West (2002). Generalized method of moments and macro-economics. *Journal of Business and Economic Statistics* 20, 460-469.
- Hamilton, J. D. (1994). *Time Series Analysis*, Princeton University Press.
- Hsieh, C.-H. A., H.-C. Chou, K. Lin and D. C. Yen. (2013). Trade-off relationship between the hire and exercise prices of purchase options in ship charter contract: an option pricing application. *Journal of Marine Science and Technology* 21, 268 -277.
- Kavussanos, M. G. (1996). Price risk modeling of different size vessels in the tanker industry using autoregressive conditional heteroscedastic (ARCH) models. *The Logistics and Transportation Review* 32, 161-176.
- Kavussanos, M. G. and N. K. Nomikos (1999). The forward pricing function of the shipping freight futures market. *The Journal of Futures Market* 19, 353-376.
- Kavussanos, M. G. and I. D. Visvikis (2006). Shipping freight derivatives: a survey of recent evidence. *Maritime Policy and Management* 33:233-255.
- Keys, B. J., T. Mukherjee, A. Seru and V. Vig (2010). Did securitization lead to lax screening? Evidence from subprime loans. *Quarterly Journal of Economics* 125, 307-362.
- Koop, G. and L. Tole (2013). Modeling the relationship between European carbon permits and certified emission reductions. *Journal of Empirical Finance* 24, 166-181.
- Liu, L. M., G. B. Hudak, G. E. P. Box, M. E. Muller and G. C. Tiao (2004). Forecasting and time series analysis using the SCA statistical system. *Scientific Computing Associates Corporation*. 1, 5.44-5.46.
- Liu, L. M., G. E. P. Box and G. C. Tiao (2005). Forecasting and time series analysis using the SCA statistical system. *Scientific Computing Associates Corporation* 2, 4.4-4.11.
- Lütkepohl, H. (1985). Comparison of criteria for estimating the order of a vector autoregressive process. *Journal of Time Series Analysis* 6, 35-52.
- Nelson, C. R. and C. I. Plosser (1982). Trends and random walks in macro-economic time series: some evidence and implications. *Journal of Monetary Economics* 10, 139-162.
- Nicolás, G., Z.-G. Ana and G.-B. María Antonia (2015). Complaints management and bank risk profile. *Journal of Business Research* 68, 1599-1601.
- Stock, J. H. and M. W. Watson (2001). Vector autoregressions. *Journal of Economic Perspectives* 15, 101-115.
- Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics* 6, 461-472
- Tiao, G. C. and R. S. Tsay (1983). Multiple time series modeling and extended sample cross-correlations. *Journal of Business and Economic Statistics* 1, 43-56.
- The Baltic Exchange. (2015). Index summary. <http://www.balticexchange.com/market-information/indices/>.
- United Nations Conference on Trade and Development (UNCTAD) (2009-2015), *Review of Maritime Transport*. New York and Geneva.