Journal of Marine Science and Technology, Vol. 26, No. 5, pp. 692-702 (2018)
DOI: 10.6119/JMST.201810_26(5).0008

PERIODICAL CHARACTERISTICS OF SHIPBUILDING MARKET ACTIVITY: A WAVELET ANALYSIS

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Key words: shipbuilding market, shipping, cycle, wavelet analysis, forecast.

ABSTRACT

Shipbuilding, a significant sector of the international shipping market, shows fluctuations and periodicity typical of variations in supply and demand. However, it takes a significant amount of time to build a ship, and the influencing factors are complex. Therefore, attempts to understand the market's fluctuations by directly analyzing these influencing factors suffer from high inaccuracy, necessitating a quantitative analysis of shipbuilding's periodic features. In this paper, we used wavelet analysis, an efficient way to analyze time series data, to analyze the unit price of a Panamax bulk ship's compensated gross tonnage and get the periodical features of the market. Choosing a significantly periodic wavelet coefficient curve yields three different cycle lengths: a 1-year seasonal cycle, a 3.5-year short-term cycle, and a 13-year medium-to-long-term cycle. Finally, we analyzed the accumulated wavelet coefficient curve, and forecasted that the market should reach its next prosperity phase around 2023 in the medium-to-long-term cycle. The present study is in the direct interest of maritime practitioners, because it helps to more precisely forecast shipbuilding market fluctuations, allowing them to make informed decisions

I. INTRODUCTION

It is widely acknowledged that the international shipping industry, which facilitates more than 90% of world trade transports (Chang et al., 2010), is tightly linked to the global economy. As the derived demand of international trade, the shipping market both serves international trade and reflects the development and tendency of the international economic environment. Thus, the shipping market possesses periodical variations, and it is in the best interests of researchers to conduct myriad studies investigating the dynamic and volatile characteristics of the market for financial purposes (Yin et al., 2017). Due to long construction periods, high capital investment, and long investment payback periods, the shipbuilding industry's decision-making is high-risk (Adland, 2017). The periodic fluctuation of the shipbuilding market is also influenced by freight rates, the supply of ships, building costs, etc. (Xu, 2011).

Currently, the shipping market is in its "winter season." With the slumping of 95% of the BDI (Baltic Dry Index) in the half-year of 2008, the unit price of the shipbuilding market also dropped 56% compared to its peak value in 2008. Meanwhile, weak recovery of the world economy in recent years coupled with constant deliveries of a large numbers of new-built ships that were ordered before the outbreak of the international financial crisis, has resulted in a significant depression in the shipping market (Du et al., 2017). To bolster themselves against this weak phase in the shipping market, some shipping enterprises chose to merge, and shipyards largely chose to reorganize (Mclaughlin and Fearon, 2013). Therefore, the importance for analysts and policy makers to be able to accurately forecast the volatility and dynamicity of the shipbuilding market cannot be exaggerated.

An abundance of researches have attempted to understand the time-varying characteristics of freight rate volatility by focusing on some of its determinants (Kavussanos and Alizadeh-M, 2002). Other researchers have attended to the correlation and influence mechanisms between markets and influence factors (Dai et al., 2015; Ahmadi et al., 2016; Dimitris, 2016). Gkochari (2015) analyzed a dataset of the Capesize market based on option games that helped to explain the existence of boom-and-bust cycles in shipping. Gong and Lu (2013) applied the stochastic volatility model to analyze the daily price of the Panamax forward freight agreement from 3 Jan. 2006 to 13 Aug. 2010, suggesting that stabilities, volatility persistence, and the trading active degrees all varied under different conditions. Raju et al. (2016) used the GARCH and EGARCH methods to analyze shipbuilding prices for LNG (liquefied natural gas) carriers, and found

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significant volatility of the prices; they also revealed that negative shocks were more persistent than positive shocks. Alizadeh (2013) investigated the price volatility and trading volume relationship in the forward freight agreement (FFA) market for dry bulk ships over the period 2007-2011, the results showed a positive contemporaneous relation between volatility and trading volume and that lagged price volatility had a negative effect on FFA trading volume.

A significant amount of research focused on the development trends in the shipping market (Duru, 2012). Kou et al. (2014) investigated the lead-lag relationships between new-built and second-hand ship prices, the results showed that the division of the ships' type greatly influenced the direction of the lead-lag relationship between two ship prices. Cullinake (1992) developed a BFI (Baltic Freight Index) forecasting method with the ARIMA model. Since then, some prediction techniques, such as statistical regression (Veenstra and Franses, 1997) and neural networks (Li and Parsons, 1997) had been used to forecast the shipping market. The periodic characteristics were also considered when predicting the market tendency. Kavussanos and Alizadeh-M (2001) investigated the seasonality of dry bulk freight rates, measuring and comparing it across freight rates of different vessel sizes. Their results illustrated that spot rates for larger vessels exhibit higher seasonal fluctuations than those for smaller vessels, and they attributed asymmetries in seasonal fluctuations in freight rates over different market conditions to the high and low elasticities of supply.

In researching periodic characteristics of the shipping market, Goulielmos and Siropoulou (2006) used the rescale range analysis method to calculate the duration of cycles manifested in the prices of second-hand tanker ships, finding the existence of two cycles of tanker ship prices with durations of 4 and 8 years. Those results were, of course, preliminary; much more data was required to test their forecasting validity, and this should be regarded as only a starting point in this provocative area of research. Kavussanos and Visvikis (2004) used a single-variable seasonal ARIMA-SARIMA model, multivariable seasonal cointegration, and VAR model to analyze the seasonal characteristics of the dry bulk shipping market. Ascarsi (2007) analyzed how the dry bulk market's periodic variations influenced decision-making on the ship owners' side, however, the results failed to forecast the length and variation of the cycle.

Stopford (2009) published a famous study of the shipping market cycle. He described the periodic variations and elaborated the formation mechanism of the shipping market cycle, meanwhile, divided the market into four phases: trough phase, recovery phase, crest phase, and decline phase. The results proposed three kinds of cycles in the shipping market: a long cycle (about 60 years), a short cycle (5 to 10 years), and a seasonal cycle (less than 1 year). By analyzing the characteristics and formation mechanisms of the shipping market cycles from 1741 to 2007, he found a descending trend in the short cycles, which ran every 14.9 years from 1741 to 1771, 9.2 years from 1871 to 1937, and 8 years from 1947 to 2007. However, no adequate method was provided for forecasting the cycle length in his research. In this paper, we follow this practice of dividing the cycles into three different time-scales in order to analyze the market periodic features more precisely.

Despite all of this research, there remains a dearth of precise quantitative studies specially for the shipping market cycle, particularly for the shipbuilding market, which must contend with the prolonged time required to build a ship and must therefore consider long-term market variations. Since empirical methods failed to meet these requirements, a quantitative study of periodic variations should be introduced to lend guidance to enterprise decision-making, such as whether to build new ships in the low-tide period of the shipbuilding market.

Research on shipping market data mainly focused on the forecasting of the BDI using an extensive number of prediction methods (Duru, 2012). These methods typically attempted to define periodical features. Papailias et al. (2017), for example, investigated the BDI with comprehensive forecasting performance evaluation methods, finding that there existed a strong pattern of cycle duration of between 3 and 5 years, and that this pattern was relatively stable across time. However, the results from each were quite different due to the complexity of the influencing factors in the shipping market.

In this paper, we use wavelet analysis to focus on the shipbuilding market's periodic characteristics (especially the cycle length) and forecast the market's future variations. Wavelet analysis is particularly suitable for the time-frequency scale of the data. Thus, we chose the Panamax shipbuilding market as our case study because the Panamax bulk is a typical type of ship which can voyage on most lines. First, to minimize the influence of disorderly factors, we denoise the unit price data for the Panamax bulk ship's compensated gross tonnage (CGT) from Jun. 1976 to Feb. 2017. At the same time, the data in the boundary is expanded to eliminate the boundary effect. Second, we use the *db*4 wavelet function to process the data with a one-dimensional continuous wavelet transform and obtain different wavelet coefficient curves. Since the wavelet coefficient curves' time-frequency distribution (TFD) variation features are consistent with the original data's TFD variation features, we select the wavelet coefficient curves with significant periodic features to analyze the original data's periodic features. Finally, we reconstruct the wavelet coefficient curves with different TFD variation features to characterize the periodic variation in three different time-scales. Our research's contributions can be described as follows:

(1) Building a framework to analyze the periodic variation characteristics of the shipbuilding market based on a wavelet analysis.
(2) This paper divides the cycles into three typical time-scales in order to research different cycles' features. After that, we reconstruct wavelet coefficient curves for the three time-scales based on the calculated cycle lengths to forecast periodic variations and the tendency of the shipbuilding market, in contrast to former wavelet analysis research that only analyzed data in one time-scale. This process makes the analysis of the shipbuilding market's periodical vari-

ation characteristics more precise.

(3) Using quantitative methods to analyze the shipbuilding market's cycle length and forecasting future periodical variations in the shipbuilding market, in this way, we establish a theoretical basis and framework to analyze the shipping market's periodic variation features using wavelet analysis, and give guidance to the decision-marking of the shipping market's enterprises and policy makers.

The rest of the paper is organized as follows: Section 2 introduces the wavelet analysis method and the *dbn* wavelet function; Section 3 describes the data; Section 4 discusses the results of the wavelet analysis and the forecasting of the periodic variation and tendency during the next medium-to-long-term cycle. The article is summarized in Section 5.

II. METHODOLOGY

In 1974, J. Morlet put forward the theory of wavelet analysis, which localizes the time and frequency of the analysis function (Daubechies and Heil, 1992), providing a better way to analyze non-stationary time series (Daubechies, 1990). Currently, wavelet analysis is widely used in time series research in fields such as geophysics (Kumar and Foufoula-Georgiou, 1997), hydrology (Sang, 2013), climatology (Kwon et al., 2007), finance (Cazelles et al., 2008), and statistics (Abramovich et al., 2000). Wavelet analysis can be performed locally on a signal, as opposed to the Fourier transform, which is inherently nonlocal due to the space-filling nature of its trigonometric functions (Farge, 1992). Many traditional method, such as ARIMA and VAR models require data to be stationary and the residual is white noise (Zeng et al., 2016), while the wavelet transform is capable of representing time and frequencies simultaneously so that it can be used to analyze non-stationary data. Wavelet analysis can also indicate the periodic variation features in the original data at different time and frequency scales and provides theoretical support for forecasting variations in a market's future (Astaf'eva, 1996). Consequently, wavelet analysis was used to analyze three time-scale cycles.

The core idea of wavelet analysis is to use a wavelet function to represent or approximate original signals or functions; thus, it is crucial to choose an appropriate wavelet function (Debnath and Shah, 2002). In practical research, wavelet functions are usually determined by their characteristics and empirical results (Ahuja et al., 2005), obtaining the wavelet coefficient through the wavelet transform. Wavelet coefficient curves reflect the variation features of the original data in different time-frequency scales. Consequently, we can select wavelet coefficient curves with significant periodic features to analyze the original data's periodic features.

The case study's object is the building price of a Panamax bulk ship, which shows unordered fluctuations under the influence of periodic and non-periodic factors. There is a high frequency of non-periodic factors, which are usually random, in the data. Therefore, we decompose the data based on a wavelet analysis and reconstruct the low-frequency signals that indicate the periodic features of the data. We then analyze the market's periodic variation features in combination with the variation features in the high-frequency signals.

1. Wavelet Function

The wavelet function is obtained by stretching and translating a mother wavelet. Hence, the wavelet function has fluctuating features and can quickly decrease to zero. The mother wavelet function $\varphi(t)$ satisfies the follows equation:

$$\int_{-\infty}^{+\infty} \varphi(t)dt = 0, \varphi(t) \in L^2(R) \tag{1}$$

Furthermore, the wavelet function's Fourier transform $\varphi(w)$ satisfies the condition:

$$\int_R \frac{|\varphi(w)|^2}{w} dw < \infty \tag{2}$$

where $\varphi(t)$ is the mother wavelet function, which can form a multigroup function system through the transform of stretching and translating.

$$\varphi_{a,b}(t) = |a|^{-\frac{1}{2}} \varphi\left(\frac{t-b}{a}\right), (a, b \in R, a \neq 0) \tag{3}$$

where $\varphi_{a,b}(t)$ is the wavelet function, a is the scale factor that shows the cycle length of the wavelet, and b is the translation factor that shows the translation value of time. In practice, we should choose a suitable mother wavelet for each research situation; analyzing the same data with different wavelet functions would yield quite different results. Researchers usually combined empirical results with experiments to find the error between experimental results and the theoretical analysis results.

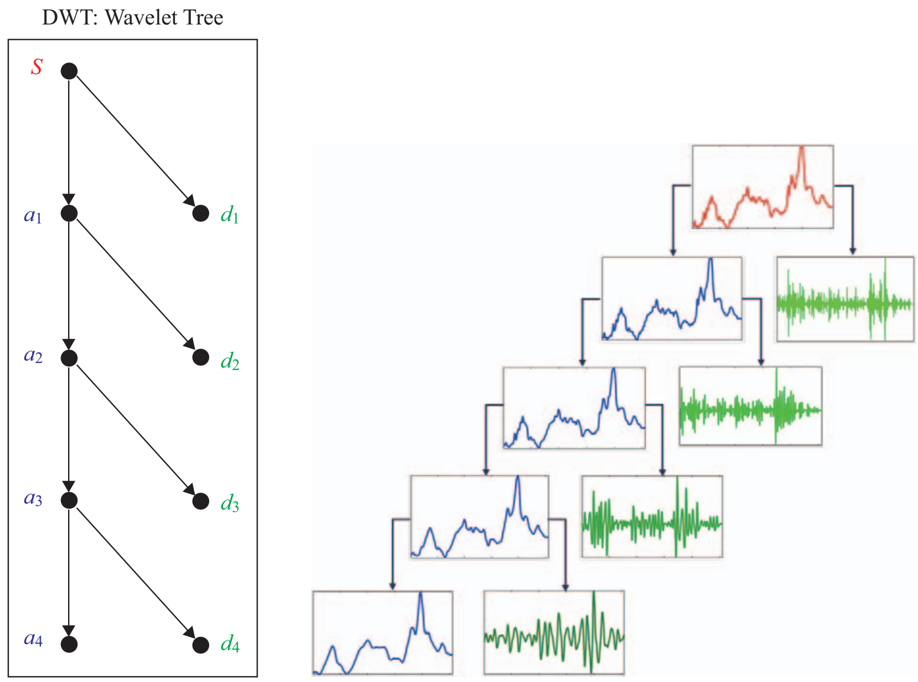
2. Wavelet Transform

A wavelet transform is the development and extension of the Fourier transform. It differs from the Fourier transform, which transforms the analyzed function into only the frequency-domain, in that it can transform a one-dimensional time-domain function into a time-domain and a frequency-domain. In general, wavelet transforms can be used to explore, denoise, and smoothen time series, aiding in forecasting analysis (Lindsay et al., 1996).

If $\varphi_{a,b}(t)$ is the mother wavelet in function (3), for the finite energy signal $f(t) \in L^2(R)$, its continuous wavelet transform formula can be shown as:

$$W_f(a, b) = |a|^{-\frac{1}{2}} \int_R f(t)\overline{\varphi}\left(\frac{t-b}{a}\right)dt \tag{4}$$

where $f(t)$ is the signal function whose square can be integrated, a is a scale factor, b is a translation factor, while



(a) Wavelet tree (b) Four-layer decomposition: $S = a_4 + d_1 + d_2 + d_3 + d_4$

Fig. 1. Four-layer wavelet decomposition of the unit price of a Panamax bulk ship's *CGT*. (Data Source: Clarkson SIN).

$\bar{\varphi}\left(\frac{t-b}{a}\right)$ and $\bar{\varphi}\left(\frac{t-b}{a}\right)$ are complex conjugate functions.

If the original signals are discrete time series data, assuming the function $f(k\Delta t)$ with $k = 1, 2, \ldots, N$ and Δt as the interval of the data points, then the discrete wavelet transform function can be shown as follows:

$$W_f(a, b) = |a|^{-\frac{1}{2}} \Delta t \sum_{k=1}^{N} f(k\Delta t)\bar{\varphi}\left(\frac{k\Delta t - b}{a}\right) \tag{5}$$

Through the wavelet transform of (4) or (5), the wavelet analysis can obtain high and low frequency signals by changing the scale factor (a). Then the global and local signals can be analyzed, and the signal's features at different time-frequency scales can be obtained.

Fig. 1 shows the wavelet decomposition process for the unit price of a Panamax bulk ship's *CGT* data; the details of the data are introduced in the data description part. The first layer shows the process of decomposing the original signal S (the unit price of a Panamax bulk ship's *CGT*) into a low-frequency layer a_1 and a high-frequency layer d_1, then decomposing the low frequency layer a_1 into a_2 and d_2 with the same step size. In this way, we obtained four layers ($S = a_4 + d_1 + d_2 + d_3 + d_4$), as shown in Fig. 1. The high-frequency layer reflects the influence of random disturbance factors, and the low-frequency layer reflects the periodic features of the original data. If the original signals (S) are large enough, S can always be denoted as: $S = a_1 + \sum_{i=1}^{i} d_i$.

The shipping market shows disordered fluctuations on account of the periodic and non-periodic influencing factors. The random disturbance factors, which show high-frequency features due to their randomness, can be clearly identified and separated. Accordingly, we can investigate the shipbuilding market's periodic variation features by using wavelet analysis to reconstruct the low-frequency layers, which show the periodic features, and combine that information with an analysis of the variation features in the high-frequency layers.

3. Daubechies (*dbn*) Wavelet Function

The Daubechies wavelet function was proposed by Ingrid Daubechies. It has no definite functions except *db*1, which is same as the Haar wavelet function. The *db*1 can be written as:

$$\psi_H = \begin{cases} 1, \ 0 \le x \le \frac{1}{2} \\ -1, \ \frac{1}{2} \le x \le 1 \\ 0, \ else \end{cases} \tag{6}$$

The main features of the *dbn* wavelet function include: the effective bracing length of the wavelet function is $\varphi(t)$ with a scale function of 2N-1; the wavelet function's vanishing moment degrees are N; *dbn* functions are mostly asymmetrical; the regularity increases with the growth of N; and *dbn* functions have an orthogonality feature.

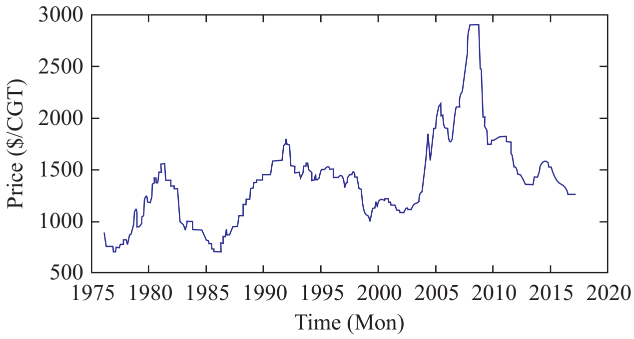


Fig. 2. Chart of the unit price of a 70K *DWT* Panamax bulk ship ($/*CGT*). (Data Source: Clarkson SIN).

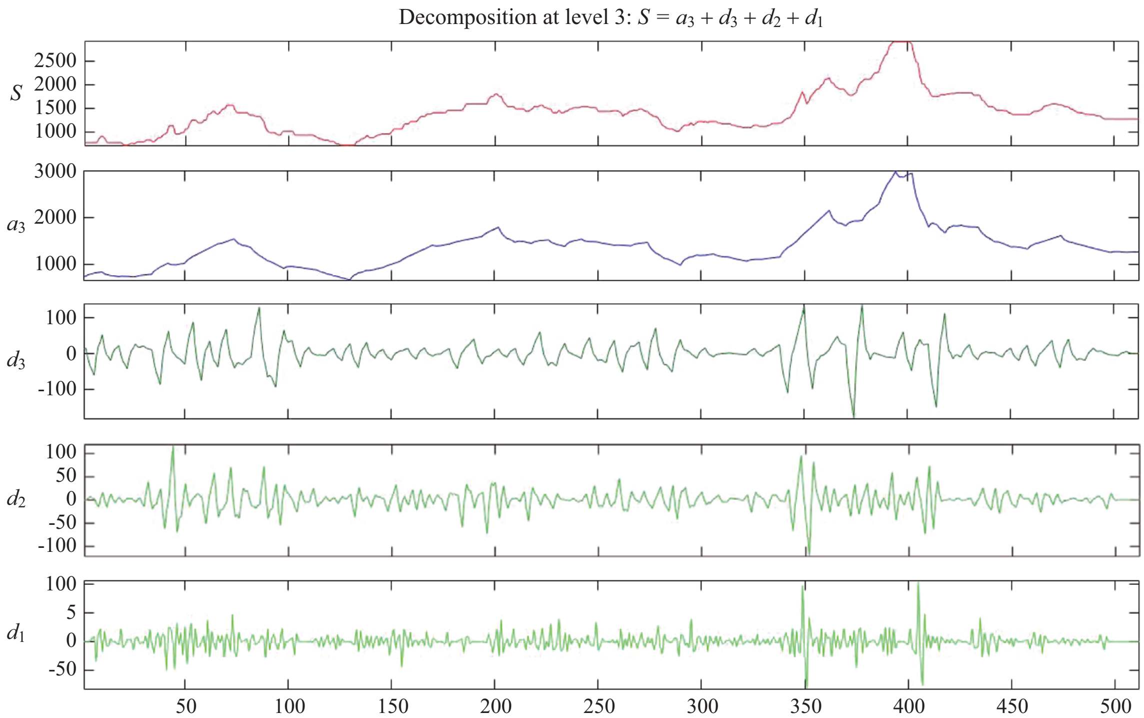


Fig. 3. Wavelet decomposition of the Panamax *CGT*'s unit price through *db*2.

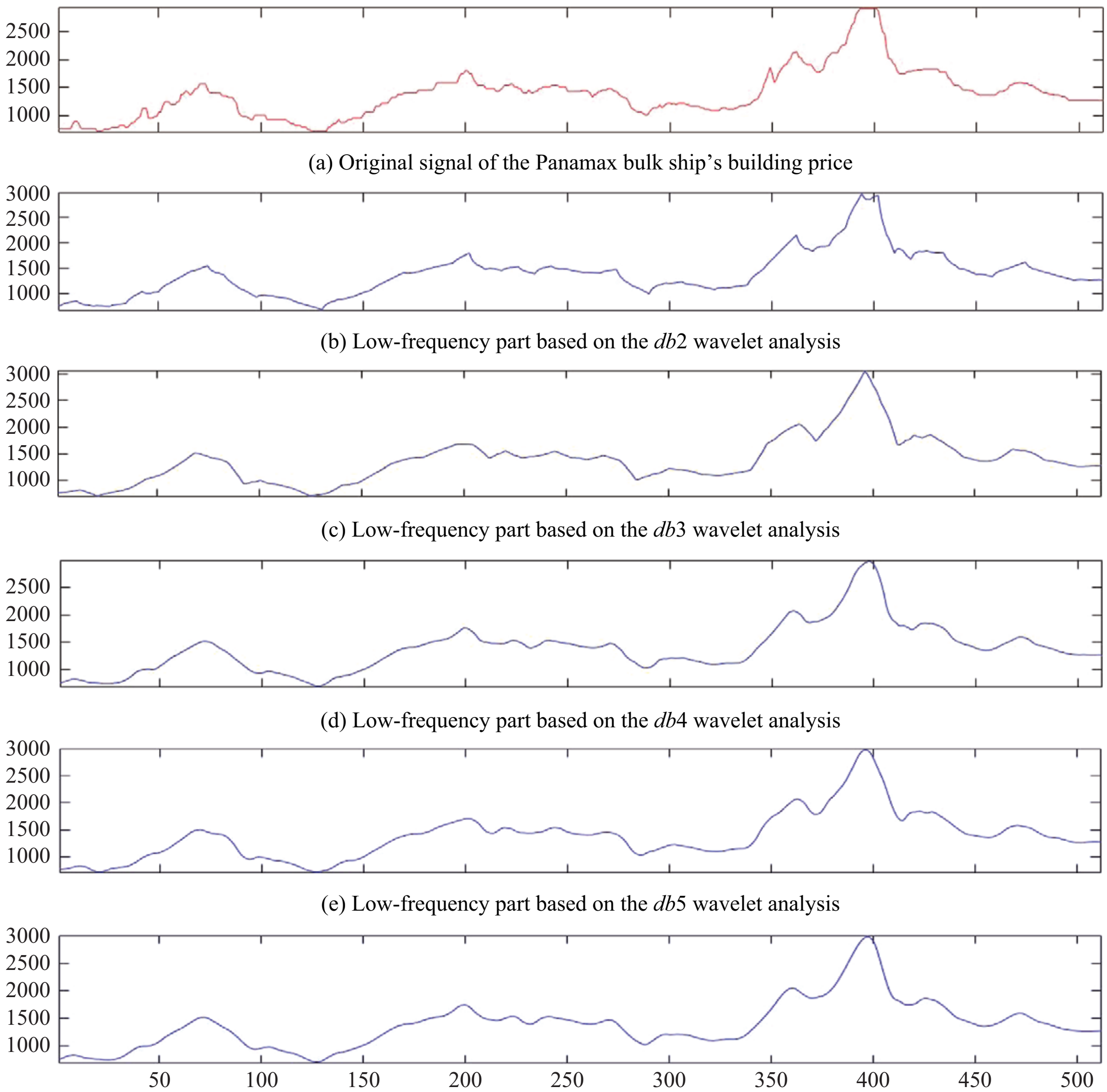
III. DATA DESCRIPTION

In this paper, the typical Panamax bulk ship was selected as a case study for the shipbuilding market. The bulk ship is the main ship type because it transports raw materials such as ore and grain which cover the majority of the shipping trade's freight volume. Thus, the 70K DWT Panamax bulk ship was selected as the most practical for a case study of shipbuilding market activity. Considering the difference in shipping structure, the unit price of the dead weight ton or gross ton cannot adequately reflect a shipbuilder's workload. Hence, it is better to use the *CGT*, which uses correction factors to reflect the relationships among the workload, outputs, and price of the ship. To find the relationship between the seasonal price and annual price, we obtained the monthly data for the unit price of a 70K DWT Panamax bulk ship ($/*CGT*) from Jun 1976 to Feb 2017 from the database of the Clarkson SIN (Fig. 2).

IV. RESULTS AND DISCUSSION

1. Selection of the Wavelet Function for the Panamax Shipbuilding Market

Analysis of historical data reveals four typical periodic features in the dry bulk shipping market: a recovery period, crest period, decline period, and trough period. Furthermore, the medium-to-long-term cycle consists of seasonal cycles. In terms of the shipping market's fluctuation characteristics, the low-frequency part of the data reflects the market's periodic variation features, and the high-frequency part reflects the influence of random disturbance factors. However, using different wavelet functions yields quite different results; therefore, we combine the reference and experimental data to select the wavelet function that best



(a) Original signal of the Panamax bulk ship's building price

(b) Low-frequency part based on the *db*2 wavelet analysis

(c) Low-frequency part based on the *db*3 wavelet analysis

(d) Low-frequency part based on the *db*4 wavelet analysis

(e) Low-frequency part based on the *db*5 wavelet analysis

(f) Low-frequency part based on the *db*6 wavelet analysis

Fig. 4. Comparison of the low-frequency part based on *dbn* wavelet analyses (n = 2, 3, …6).

reflects the variation features of the original data.

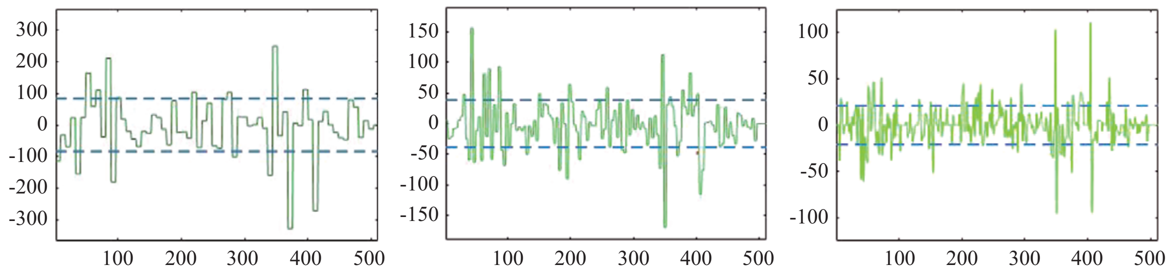
A large numbers of mother wavelet functions with different characteristics were used for various kinds of research (Ma et al., 2003; Vonesch et al., 2007; Rafiee et al., 2009). We selected them for this analysis since dbn wavelet functions are widely used to analyze time series data (Percival and Walden, 2006).

Fig. 3 shows the three-layer decomposition of the original data based on the *dbn* wavelet function with a value of $n = 2$. We select the a_3 layer (low-frequency layer) to contrast with the original data layer. Satisfactory conformity was found between the reconstitution of the low-frequency data and the original data. Concurrently, some of the interference factors are eliminated by removing the high-frequency layers. These results confirm the validity of the *dbn* wavelet function we selected for this paper.

2. Selection of the Wavelet Vanishing Moments for the Panamax Shipbuilding Market

Inherent in the *dbn* wavelet function's features is the possibility that the function could increase with the growth of the vanishing moments. Additionally, the function has the capacity for data localization in the frequency domain; however, at the same time, its capacity for compact support would decrease in the time domain. Accordingly, we choose several different n values (n = 2, 3, …6) and use the *dbn* wavelet function to decompose the original signal into three layers, then we compare the low frequency layer (a_3) with the original signal layer (S).

As shown in Fig. 4, with the increase of n, the low-frequency curve obtained becomes smoother, and the data become more stable. However, it also becomes more difficult to recognize the periodic features. Thus, we chose the *db*4 wavelet function



(a) Denoising of $d3$ layer (b) Denoising of $d2$ layer (c) Denoising of $d1$ layer

Fig. 5. Denoising of Panamax *CGT* price data.

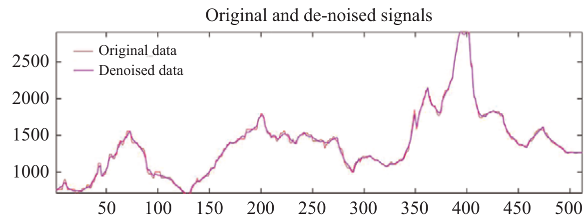


Fig. 6. Comparison of the denoised and original curves for the Panamax *CGT* price.

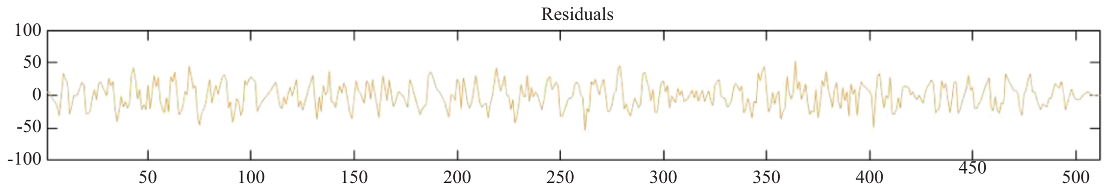
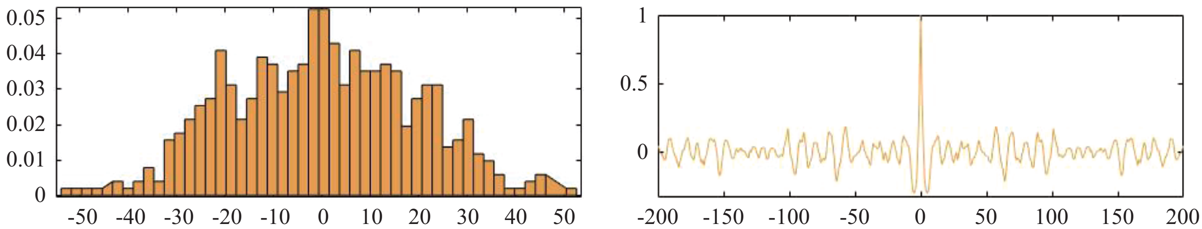


Fig. 7. Residuals curve for the Panamax *CGT* price.



(a) Histograms (b) Autocorrelations

Fig. 8. Panamax bulk ship's residual analysis based on monthly data.

as the one that best denoises the original signals smoothly without losing too much detail.

3. Denoising the Unit Shipbuilding Price of the Panamax *CGT*

By denoising the original data through the wavelet analysis, we reduce the random-factor disturbances and reveal the trend and periodic variations. First, we exclude the variation value in the high-frequency layers by setting a threshold value (Fig. 5). Then, we reconstruct the denoised high-frequency layers with the a_3 layer. As shown in Fig. 6, the denoised curve becomes smoother, which demonstrates that the random disturbance factors in the original data have been effectively eliminated.

The residual analysis finds no tendency in the residuals curve (Fig. 7). The histograms have a desirable symmetry (Fig. 8(a)). Furthermore, the autocorrelation curve is under 0.2 without the midsection, which shows that the residuals have satisfactory randomness (Fig. 8(b)). In conclusion, our denoising process reaches an ideal condition.

4. Forecasting the Panamax Shipbuilding Market's Cycle Length Based on a One-Dimensional Continuous Wavelet Analysis

We obtain a wavelet coefficient map based on a one-dimensional continuous wavelet analysis of the monthly data (Fig. 9). The

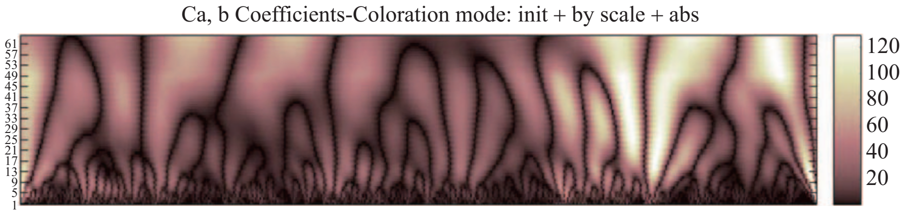
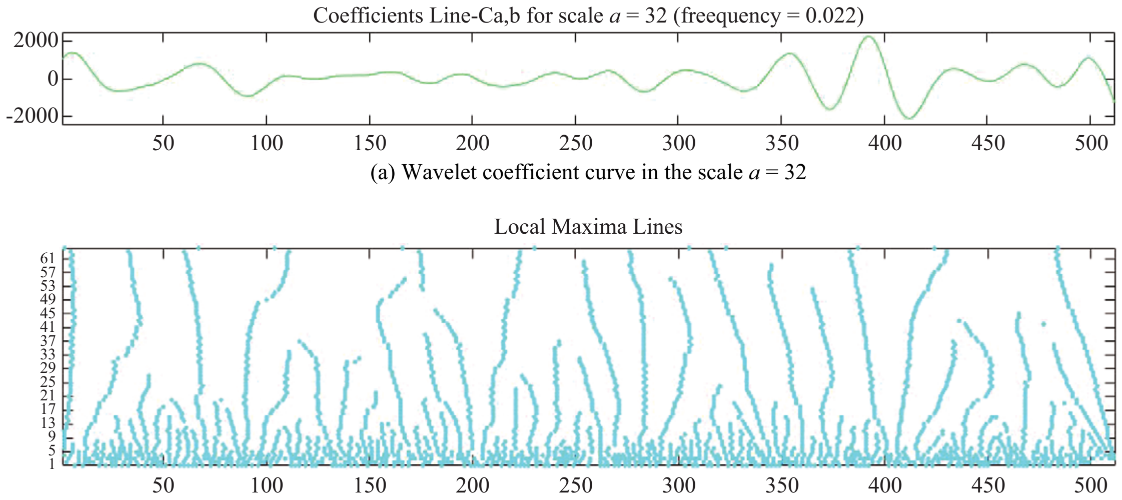


Fig. 9. Wavelet coefficient map of the Panamax *CGT*'s monthly price.



(a) Wavelet coefficient curve in the scale a = 32

(b) Local maxima lines

Fig. 10. Wavelet coefficient curve in the scale a=32 and local maxima lines from the wavelet coefficient map.

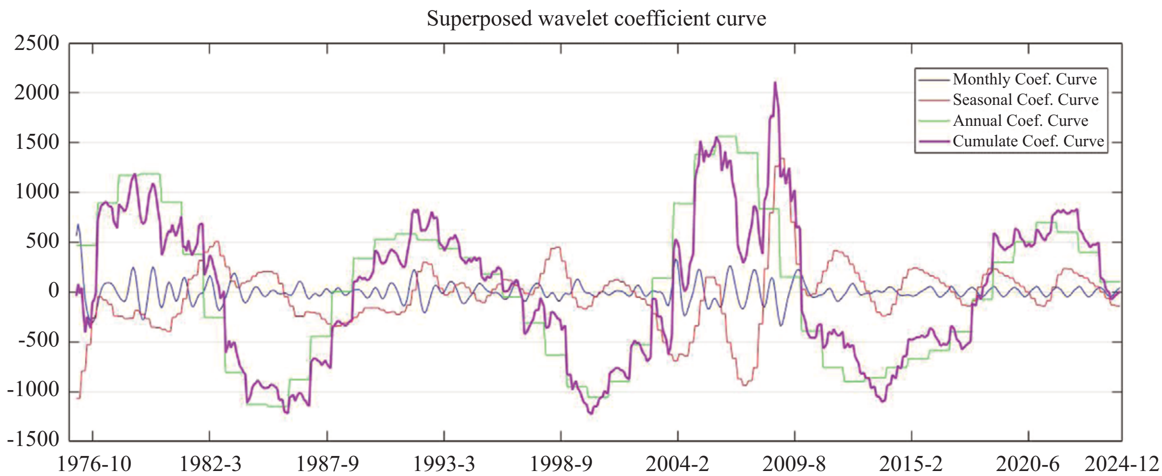


Fig. 11. Superposed wavelet coefficient curve for the Panamax unit *CGT* price.

wavelet coefficients in the map periodically show dark and bright changes, and the intervals between them vary on different scales (shown in the vertical coordinates). In general, the map can be divided into three layers: a medium-to-long-term cycle (scales from 38 to 64), a short cycle (scales from 14 to 37), and a seasonal cycle (scales from 0 to 13).

Fig. 10 shows the wavelet coefficient curve in the scale a = 32 and the local maxima lines of the wavelet coefficient map. From those results, we obtain the wavelet coefficient curve that minimizes the variances of the interval. The best scale in the monthly data is 8, and the frequency of the coefficient curve is 0.089. Because the cycle is the reciprocal of the frequency, we ascertain that the seasonal cycle is 11.2 months. Using the same method to process the seasonal and yearly data, we determine

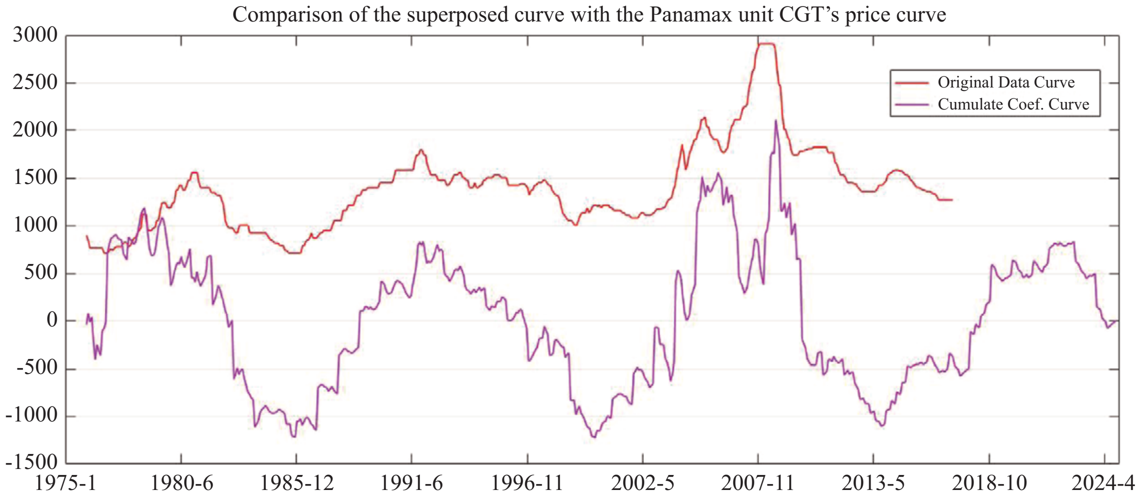


Fig. 12. Comparison of the superposed curve with the Panamax unit *CGT* price curve.

that the short cycle is 12.6 quarters (3.1 years). Using the scale a = 32 in the monthly data, we find a cycle length of 45.4 months (3.9 years). Therefore, we establish a 3.5-year short cycle based on the mean value. Considering the small size of the yearly data, considerable errors result from selecting only one scale to represent the cycle. Hence, we select the scales $a = 8$, $a = 9$, and $a = 10$ and calculate the mean value, which produces the 12.7-year medium-to-long-term cycle.

5. Forecasting the Panamax Shipbuilding Market's Periodic Variations

Considering the influence of the data boundary effect, we extend the data to Dec. 2017 using the value from Feb. 2017, thereby eliminating the abnormal vibrations of the cycle at the data boundary. We extend the wavelet coefficient curves based on the cycle length and the local symmetry of each cycle, in addition to extending the curves to the decline phase of the next medium-to-long-term cycle: 2024. We then establish a superposed wavelet coefficient curve (Fig. 11).

As shown in Fig. 12, there is a significant correlation of fluctuation between two curves, and the cumulated coefficient curve illustrates three different periodical features of the original data. According to the predicted superposed curve from Mar. 2017 to Apr. 2024, the curve's fluctuations reveal that the Panamax shipbuilding market would maintain its low level until around Jun. 2017 and then enter the recovery phase of the seasonal cycle. Meanwhile, the market would maintain its low level through around the third quarter of 2017 and then enter the recovery phase of the short cycle. Furthermore, the market is forecasted to enter the recovery phase of the medium-to-long-term cycle after 2018 and reaching its flourishing phase around 2023. At present, the market's general tendency continues to be the further reduction of surplus capacity. With this in mind, the amplitude fluctuation of the market is relatively small, and the market presents a slow-growth tendency.

The periodic interval of the monthly data's wavelet coefficient curve (Fig. 13) presents the periodical vibrations and retracting transformations and is correlated with world business cycle variations (Zhang et al., 2014). Since 1976, the cycle can be divided into seven phases according to the size of the amplitude: 1976-1984, 1984-1990, 1990-1999, 1999-2003, 2003-2010, 2010-2016, and after 2016. Those results are in accord with those of Yang et al. (2013), who used a vector auto-regression model to divide the world business cycle into 5 phases since 1980.

The predicted Panamax shipbuilding market's seasonal cycle is 11.2 months, as ascertained from the monthly data. The seasonal cycle reflects the market's periodic variations within the unit of the month and accords with the law of seasonal changes. The cycle measured according to the recent crest from Jan. 2016 to Jan. 2017 is 12 months, which is similar to the predicted value. The cycle length of 11.2 months also reflects the disturbance of disorderly factors, which break the typical 1-year nature cycle.

Meanwhile, the predicted short cycle is 3.5 years. The estimated cycle is 3.6 years according to the latest wave crest (from the third quarter of 2011 to the second quarter of 2015), and the latest wave trough (from the second quarter of 2010 to the fourth quarter of 2013), which approaches the forecast value. The main reason for the formation of the short cycle might be the superposition of relatively strong influencing factors that break the medium-to-long-term cycle and factors that have a similar cycle length, such as the shipbuilding period.

Finally, the predicted medium-to-long-term cycle is 12.7 years, as shown in Fig. 13, which has a significant correlation with world business cycle variations. The mean value of the periods is about 13 years, and the shipbuilding market from 2003 to 2016 (13 years) went through a flourishing phase from 2003 to 2007, a decline phase from 2007 to 2010, and a trough phase and recovery phase after 2010.

V. CONCLUSION

In this study, we researched the shipbuilding market's pe-

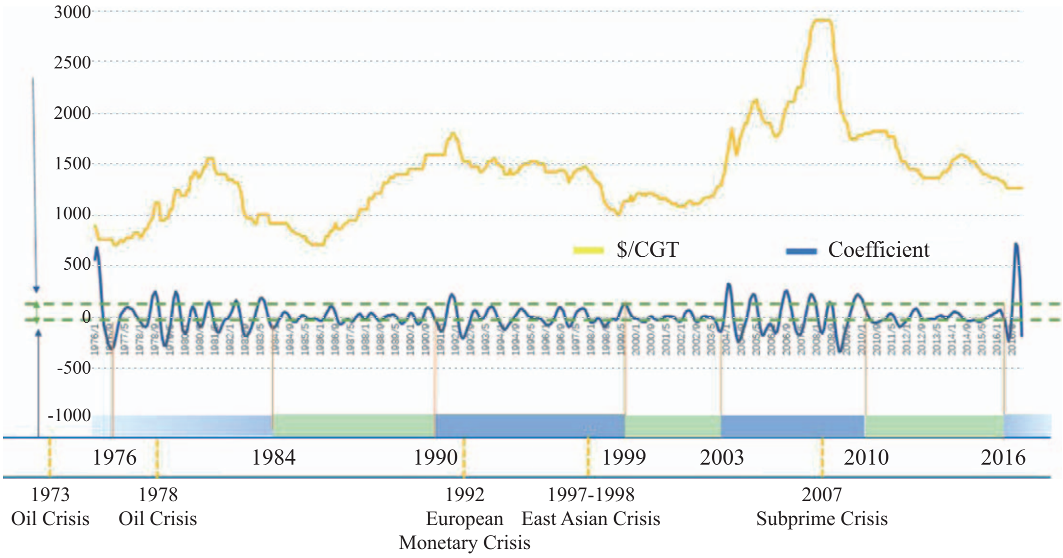


Fig. 13. Panamax unit *CGT* price curve and monthly wavelet coef. curve in the scale *a* = 8.

riodical characteristics and presented a framework for a cycle analysis of the shipbuilding market based on wavelet analysis. First, we introduced the wavelet analysis method and *db*4 mother wavelet. Second, we collected data on Panamax unit *CGT* prices from Jan. 1976 to Feb. 2017. Third, we established three wavelet coefficient curves on different time-scales to analyze the market's periodic features based on wavelet analysis, and we forecasted the Panamax shipbuilding market's periodic variations through an analysis of the wavelet coefficient curves. In summary, the following conclusions can be made: (1) The predicted Panamax shipbuilding market's seasonal cycle is 11.2 months, the short cycle is 3.5 years, and the medium-to-long-term cycle is 12.7 years. (2) By analyzing the superposed wavelet coefficient curves, we ascertained that the Panamax shipbuilding market will enter the recovery phase of the seasonal cycle after Jun. 2017 and enter the recovery phase of the short cycle after the third quarter of 2017. Furthermore, the market will enter the recovery phase of the medium-to-long-term cycle after 2018 and reach the crest phase around 2023.

It is in the best interests of those participating in the shipbuilding market's activities to further consider its cycle's features and forecast future market variations. These periodical features can help entrepreneurs to have a better knowledge of the shipbuilding market's variations and thus more precisely forecast the market's future. Hence, these results can give guidance to decisions regarding the purchase or sale of ships by shipowners, and the construction or dismantling activities of shipyards.

The results can also help the goverment to make policies and regulations much more suitable to the needs of the shipbuilding market. For example, the tax rate could change according to the market's variations. The governor can cut the tax rate levied on entrepreneurs in the shipbuilding industry when the market is in a declining period, which is important to promote the sustainable development of the shipbuilding market. Moreover, the shipping market serves to forecast the world economy, since transportation is so closely associated with world trade. In this case, the results can also serve to predict the global economic environment.

This research primarily investigated the periodical variation features of shipbuilding market activity. Future studies could be done to study the relationships among different cycles and the formation mechanism for different cycles. A seasonal forecasting method such as seasonal exponential smoothing and ARIMA can also be used to make the forecasting more precise. In this research, we further found that the medium-to-long-term cycles are becoming shorter, while the flourishing phase's variation gradient is larger than that of the descending phase. The causes of those phenomena deserve further study.

ACKNOWLEDGEMENTS

This study is partially supported by the National Natural Science Foundation of China (Grant nos. 51879156 and 51409157), the Program of Humanities & Social Science of the Ministry of Education of China (14YJC630008), the Shanghai Pujiang Program (17PJC053), and the Shanghai Science & Technology Committee Research Project (15590501700 and 17040501700). The authors thank the reviewers and editors for their valuable comments and kind help with this paper.

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