An Application of Dynamic Factor Model to Dry Bulk Market

- Focusing on the Analysis of Synchronicity and Idiosyncrasy in the Sub-Markets with Different Ship Size -

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ABSTRACT

BDI actually has weighed more on larger-size market. So, calculating the synchronicity of dry bulk sub-markets by using BDI as reference indicator could lead to mistake. Therefore, for the analysis of synchronicity and idiosyncrasy of dry bulk markets, this paper constructs a dynamic factor model of the change rate of BDI's constituting indices and then it performs maximum likelihood estimation. One important finding is that, for such larger ships as Capesize and Panamax, there has been a significant increase in their synchronicity with global common factor after the 2008 global financial crisis, but for the other smaller ships, the opposite phenomenon has been observed.

This paper suggests two important future research topics. One is extending the suggested dynamic factor model with the structural change (regime switching). The other is constructing a new index for the level, not the change rate, of the status of global dry bulk market. The author believes that the combination of these issues could produce an alternative index to BDI.

Key words: Dry Bulk Shipping, Dynamic Factor Model, Synchronicity and Idiosyncrasy, Structural Change

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1. Introduction

The Baltic Dry Index (BDI, hereafter) has been used widely as a representative barometer for the global dry bulk market. The history of the emergency of BDI is as follows: At first, in 1985 the Baltic Exchange developed the daily freight index, Baltic Freight Index (BFI, hereafter) as a settlement mechanism for the then newly established Baltic International Freight Futures Exchange (BIFFEX) futures contract. In 1999 BDI replaced BFI. However, as the underlying asset of the BIFFEX contract, the Baltic Panamax Index (BPI, hereafter) superseded the BFI. In July 2008 Imarex (International Maritime Exchange) launched derivative contracts on the BDI as well.¹

BDI is a composite index consisting of some indices of sub-markets with different ship size, e.g., Capesize, Panamax, Supramax and Handysize. It is calculated as an equally weighted average of the sub-market indices.² So, one who is interested in the status of global dry bulk market (esp., its freight rate) may use BDI as an indicator. However, because the sub-market indices usually increase as the ship size increases, BDI actually has weighed more on larger-size market. Therefore, if we want to know the status of global dry bulk freight rate without larger-size bias, we should search for an alternative.

This paper attempts to satisfy this need of finding another indicator for the status of global dry bulk freight market. For this purpose, it adopts so-called (unobserved) dynamic (common) factor model which was introduced by Geweke (1977). This dynamic factor model usually handles a large set of time series data and extracts some small number of unobserved dynamic common factors. This technique has been used widely in macro-economics and economic forecasting. This paper attempts to extract the virtual global dry bulk factor which would affect the dry bulk sub-markets. After measuring the common factor, the idiosyncratic component of each sub-market can be calculated.

However, the limitation of this paper is large, in the sense that it cannot suggest an alternative (level) index. This paper only focuses on the change rate of the indices of sub-markets. So, it can suggest the common component of their change rates, which is assumed to exist in the global dry bulk markets. Given its limitation, this paper provides some important information for the dry bulk market participants. By analyzing a dynamic factor model, it can measure the synchronicity and idiosyncrasy of the sub-markets in a unified framework. Furthermore, rolling the estimation over the sample period after 1 July 2009 picks up a potential structural change in their synchronicity.

This paper is organized as follows: Section 2 briefly reviews some recent literature studying the dry bulk market. Section 3 explains the data set and provides the dynamic factor model of the paper. Section 4 suggests the empirical results and their interpretations.

¹ Alizadeh and Nomikos (2009), pp.108-113.

² For the modifications of the BDI calculation, see the <Table 1> below.

Finally, the section 5 summarizes the paper and suggests the future research topics.

2. Literature Review

In the below paragraphs, the paper reviews two distinct strands of literature. One studied the BDI, focusing on its determination mechanism (See Chung and Ha, 2010a; Chung and Ha, 2010b; Rim *et al.*, 2010). The other was about the dynamic properties of dry bulk markets (See Chen *et al.*, 2010; Ko, 2010a; and Ko, 2010b).

Chung and Ha (2010a) analyzed the effect of the 2008 global financial crisis on the BDI. It adopted the error correction model in the form of ARDL (AutoRegressive Distributed Lag) suggested by Pesaran, *et al.* (2001). Among their empirical results, it is an important finding that there has been a co-integration relationship between the BDI and some explanatory variables such as China's iron import, Eurodollar interest rate and U.S. stock price. Chung and Ha (2010b) further investigated the time-varying effect of China's iron import, Eurodollar interest rate and U.S. stock price on the BDI by using the Kalman filter method.³ Rim, *et al.* (2010) studied the dynamic relationship among the demand, supply and freight rate variables by using a recursive VAR model. They showed that the positive shock of the transport demand increases the future ship capacity and the BDI level. However, the positive shock of ship capacity does not influence the transport demand but does decrease the BDI level.

Chen, *et al.* (2010) investigated the interrelationship in daily returns and volatilites between Capesize and Panamax markets using the co-integration method of VECM (Vector Error Correction Model) and ECM-GARCH model. They split the sample period around the end of 2002 (or the start of 2003). Among the findings, an interesting fact is that in the second period Capesize prices tend to reflect new information more rapidly than Panamax prices. In summary, they insisted that this kind of research provides useful information for both shipowners and charterers to mitigate risks or to make extra profits by switching between the two markets.

Ko (2010a) analyzed the effect of the term structure of time-charter rates on the time-varying volatilities in the sub-markets with different ship size of dry bulk market. Inter alia, the hypothesis that there is bimodality in the supply curve of shipping freight markets is strongly supported and the fact that the market participants consider the backwardation shock in low uncertainty as more important than in high uncertainty is derived empirically. Ko (2010b) studied the change of the dynamics of dry bulk markets

³ Compared with the fact that Chung and Ha (2010b) uses the Kalman filter with time-varying coefficient model, this paper uses the Kalman filter with state-space model. For more explanation of this issue of Kalman filter, see pp.19-57 of Kim and Nelson (1999).

before and after the 2008 global financial crisis, comparing with that of pre-July 2003 when China effect was supposed to emerge. It adopted the method of 'counterfactual analysis with VAR' and showed that the main factor for the volatility reduction in some markets is the reduction of the shock itself but the main factor for the volatility increase in other markets is the increase of the shock persistence.

Among a large number of important articles on the dynamic factor models, I would like to mention a few following ones: Dynamic factor analysis in econometrics was introduced by Geweke (1977) and Sargent and Sims (1977) analyzed the main co-movement of postwar U.S. macroeconomic time series by using dynamic factor model. Stock and Watson (2008) addressed the instability issue of the dynamic factor model. This instability problem emerges due to the structural change of the considered economic system. For example, technology, policy regime and changes in the survey instruments may bring out the change of the model parameters. As shown in <Figure 1> and <Figure 2> of this paper, this instability issue is also applicable to dry bulk market. However, more in-depth analysis of the instability will remain as a future research topic. Stock and Watson (2006) explained the dynamic factor model with principal components analysis which are both interrelated closely. This work also presented some other approaches to forecasting economic variables by using a large number of dataset, for example, forecast combination (i.e., forecast pooling), Bayesian model averaging, etc. Stock and Watson (2005) examined VAR methods by using the dynamic factor models which are used to handle hundreds of economic time series. Inter alia, they provided a unifying framework that explains the implications of dynamic factor models for VAR.

In summary, the above mentioned works of Stock and Watson on dynamic factor model focuses on the macroeconomic phenomena, however. So, the application of dynamic factor model to shipping freight market in this paper can be differentiated from the previous literature.

That is, the contribution of this paper differentiated from the previous literature is that it analyzes the dynamics of BDI using the dynamic factor model, which has not been tried yet. Then, it suggests an alternative to BDI change rate as a representative index. This alternative framework makes us evaluate the synchronicity and idiosyncrasy of dry bulk markets in a unified model.

3. Data and Dynamic Factor Model

As mentioned earlier, BDI was introduced in November 1999 as the substitute for BFI. However, the calculation method changed over time. The table below shows a short history of BDI calculation.

Time	Modifications		
1 Nov. 1999	BDI replaced BFI. BDI was calculated as an equally weighted index of BPI, BCI and BHI. The factor of BDI was 0.998007990.		
2 Jan. 2001	BHMI replaced BHI. So, BHMI was used for the calculation of BDI.		
3 Jan. 2006	BSI replaced BHMI. So, BSI was used for the calculation of BDI.		
2 Jan. 2007	BHSI was used for the calculation of BDI. The multiplier of BDI changed from 0.998007990 to 1.192621362.		
1 July 2009	 BDI calculation procedure changed. BDI has been comprised solely of timecharter routes, no longer including capsize voyage routes. So, the formula has become as follows: BDI = {(CapesizeTCavg + PanamaxTCavg + SupramaxTCavg + Handy sizeTCavg)/4} × 0.113473601, where TCavg = Time Charter average. The multiplier (0.113473601) was first applied when the BDI replaced BFI, and has changed over the years as the contributing indices and the methods of calculation have been modified. 		

 Table 1. Modifications of BDI Calculation

Source: The Baltic Exchange (2010). The author excerpted and summarized.

This paper uses two data sets. One is from January 2007 to August 2008. The other is from 1 July 2009 to 18 October 2010. As shown in <Table 1>, the constituting indices of BDI differ across the two samples. For the first sample, the values of BCI, BPI, BSI and BHSI can be used as the indices. But for the second sample, the time charter averages of Capesize, Panamax, Supramax and Handysize should be used for the indices. The Clarkson website provides these averages, which were used in this paper. As a result, the data set of this paper is summarized in the following table.

Table	2.	Data	Set	Description
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Period	Data Set		
Jan. 2007 to Aug. 2008	BCI, BPI, BSI, BHSI		
July 2009 to Oct. 2010	Average of the 4 T/C Routes for Baltic Capesize Index Average of the 4 T/C Routes for Baltic Panamax Index Average BSI - Average of the 5 T/C Routes BHSI: Time Charter Average		

Source: Clarkson

Using the above data set, this paper considers the following dynamic factor model:4

⁴ The dynamic factor model of this paper is based on the model suggested in p.35 of Kim and Nelson (1999).

For $i = 1, 2, 3, 4$,	
$y_{i,t} = \mathbf{y}_i \times c_t + z_{i,t}, \qquad \qquad 1$	I)
$c_t = \varnothing \times c_{t-1} + v_t, \qquad \qquad 2$	2)
$z_{i,t} = \varphi_i \times z_{i,t-1} + e_{i,t}, \qquad \qquad$	5)
where $ \varnothing < 1$,	
$v_t \sim i.i.d.N(0,\sigma_v^2),$	I)
$e_{i,t} \sim i.i.d.N(0,\sigma_{ei}^2),$	5)

We assume that v_t and $e_{i,t}$ are all independent of one another. For the notation of *i*, *i*=1 represents Capesize, *i*=2 Panamax, *i*=3 Supramax (or Handymax), *i*=4 Handysize ship variable respectively. The variable, *y*, is the percentage change rate (measured by 100×the log difference) of the freight values, which are time-charter averages of Capesize, Panamax, Supramax and Handysize from 1st July 2009. But before 1st July 2009 they were the percentage change rate of the values of BCI, BPI, BSI, BHSI, respectively. In this model, the common factor is c_t , whose variance is set to be one for the normalization.⁵ Therefore, γ_i measures the degree of synchronicity of the individual sub-market with the common component. In contrast, $z_{i,t}$ measures the idiosyncrasy of each market.

Equations 1) \sim 5) can be expressed in the following state-space model:

⁵ This assumption of normalization means that there has been a virtual common component in the four dry bulk markets, whose variance is assumed to be $1/(1 - \emptyset^2)$. If this variance varies across the sub-samples, the difference should come from the different value of \emptyset , which captures the persistence of the common component.

Equation 6) is the measurement equation and equation 7) the transition equation (or state equation). These measurement and transition equations consist of the state-space model of this paper.

4. Empirical Results and Implications

The estimation procedure of the proposed state-space model for the dynamic factor model is well explained on pp.22-29 of Kim and Nelson (1999). A short explanation of using Kalman filter as the estimation method of the above state-space model can be provided as the consecutive two steps (i.e., prediction and updating) in the following way:

Prediction:

Given the dynamics of the system (i.e., equations 6) and 7)), predict the unobserved variable, β_t , by using the information up to the last period. In the model of the paper, there is one uncertainty from the nature of the unobserved variable. That is, because this variable cannot be observed directly, there is always uncertainty. So, calculate its (co-)variance which indicates the degree of the uncertainty.

Updating:

As the observed variable, $(\tilde{y_t})$, is realized, the new information is available. That is, from the realization of $(\tilde{y_t})$, the prediction error can be calculated and this can be used for a more accurate inference on β_t . In this step of updating, so-called 'Kalman gain' is used. However, this estimate of β_t will be used as an input for the prediction in the next period.

This prediction and updating procedure will be iterated until the estimated parameters maximize the likelihood function which is a function of the prediction errors and their (co-)variances.

For the information on the change of synchronicity after the 2008 global financial crisis, see the estimates of γ_i (i = 1, 2, 3, 4) in <Table 3>. For such larger ships as Capesize and Panamax, the synchronicity with the common factor becomes larger. Especially, Panamax shows that its synchronicity has doubled. But for Supramax (or Handymax) and Handysize, there has been a remarkable decrease in their synchronicity with common factor. However, note that the persistence of the shock of common factor, \emptyset , has decreased a little.

Classification	Jan. 2007 ~ Aug. 2008		July 2009 ~ Oct. 2010	
Classification	estimates	standard errors	estimates	standard errors
Υ1	0.65	0.255	0.93	0.092
γ_2	0.53	0.114	1.09	0.038
γ_3	0.40	0.064	0.10	0.023
γ_4	0.19	0.059	0.08	0.021
Ø	0.93	0.025	0.80	0.030
ϕ_1	0.65	0.044	0.61	0.039
ϕ_2	0.79	0.039	0.73	c.n.
ϕ_3	0.74	0.060	0.91	0.022
Φ4	0.79	0.056	0.91	0.021
σ_{e1}^2	13.98	-	3.32	-
σ_{e2}^2	1.22	-	1.62	-
σ_{e3}^2	0.41	-	0.20	-
σ_{e4}^2	0.23	-	0.17	-

Table 3. Estimates of Suggested Dynamic Factor Model

Note: c.n. means complex number Source: Author

For the idiosyncrasy, see the estimates of φ_i and σ_{ei}^2 . For the two larger ships, the persistence of idiosyncratic shock has decreased a little. For the other smaller ships, the opposite phenomenon is observed. An interesting result is that the variance of idiosyncratic shock in Capesize market has decreased by about 76%. As a result, there is a significant reduction of the variance of idiosyncratic component in Capesize market, which is compared with the results that there have been little changes in the other markets with respect to the variance of idiosyncratic component. (See <Table 4> below.)

Table 4. Change of the Variance of Idiosyncratic Component

Classification	Jan. 2007 ~ Aug. 2008	July 2009 ~ Oct. 2010	Change
Capesize	24.21	5.29	-18.92
Panamax	3.25	3.47	0.22
Supramax	0.91	1.16	0.26
Handysize	0.61	0.99	0.38

Source: Author

Up to now, the paper assumes that the parameters of the model don't change in the considered sample period. However, if we relax this assumption for the second period, there emerges an interesting phenomenon. For a concrete example, given the possibility that there could be an instability of the coefficients, γ_i , rolling the estimation in the way, in which the sample consists of 7 months and thus depleting the first observation and adding the new last one, gives us the estimates of γ_i from 1st week Jan. 2010 to now (18 Oct. 2010). The plotted estimates for the four markets are shown in the following two figures (<Figure 1> and <Figure 2>).

The dynamics of γ_i 's estimates in all the four markets strongly implies that there has been a structural change in the synchronicities of the markets. The time of a striking change is thought to be the beginning of June 2010. As of now, exceptionally the Capesize market shows a relatively high synchronicity (0.80 point) but the other three markets seem to converge to around 0.40 point in their synchronicities.



Figure 1. Evolution of Synchronicity (Cape & Panamax)



Source: Author

Figure 2. Evolution of Synchronicity (Supramax & Handysize)

Furthermore, as a bold statement, the fact that the BDI calculation simply assumes larger-ship bias could make the BDI not represent the underlying common status of global dry bulk market consisting of various sub-markets. That is, since the degree of synchronicities of individual markets could evolve, not proportionally in their ship size (or their relative level of time charter rate), there is a possibility that the equally weighted index of time charter averages of four sub-markets could not be a reference indicator to which the indices of sub-markets can be referred for the calculation of synchronicity. <Figure 3> shows that this possibility might exist in the sense that in occasion BDI change rate overestimates or underestimates the underlying common factor, given the virtual common factor suggested in this paper is the real factor governing the dynamics of global dry bulk market.

However, in spite of the above argument, the fact that the correlation between them is 0.64^6 and their means and standard deviations are almost the same implies that the BDI is a good indicator, although the underlying dynamics is the system of equations 1) ~ 5). Or as a reverse interpretation, we can say that the model of dynamic common factor captures well the properties of dry bulk markets.



Figure 3. Comparison of estimated \boldsymbol{c}_t and BDI change rate

5. Conclusion

This paper suggests an alternative measure for the status of global dry bulk market, especially focusing on the change rate, not the level, by using a dynamic factor model. For the estimation of the factor over time, it uses a state-space model and then performs the maximum likelihood estimation with the Kalman filter. Among the empirical findings,

⁶ Note that the correlation is not close to one. This implies that there is room for developing an alternative index representing the global dry bulk market.

the following three facts are worthy of mentioning: First, for such larger ships as Capesize and Panamax, there has been a significant increase in their synchronicity with global common factor after the 2008 global financial crisis, but for the other smaller ships, the reverse phenomenon has been observed. Second, the dynamics of the measures for synchronicity of considered markets shows that there has been a remarkable structural change around the beginning of June 2010. Third, there have been some occasions in which the BDI change rate overestimates or underestimates the underlying common factor, given that the virtual common factor suggested in this paper is the real factor governing the dynamics of global dry bulk market.

By the way, there are two important future research topics, which are interrelated with each other. First, modeling the structural change will be productive in that, as shown in <Figure 1> and <Figure 2>, this kind of research provides useful information on the dynamics of dry bulk market. For example, there are derivatives on BDI, BCI, BPI, etc, so this information helps the participants of these derivatives market to make more rational decision. This line of research will be the marriage of state-space models and regime switching.⁷ Second, developing an alternative to BDI as an indicator for the level of the status of global dry bulk market will be fruitful. That is, as shown in <Table 3>, because there have been some cases of divergence between the BDI rates and the virtual common factors developed in this paper, there is room for developing a new index representing the global dry bulk market. This topic can be dealt with well by the approaches of Stock and Watson (1991) and Macho, et al. (1987). The former paper deals with the topic of developing a coincident index using 4 macroeconomic variables without co-integration relationship among the considered variables but the latter paper is on the estimation of the relationship among the variables that have a common stochastic trend component, which means that there is a co-integration relationship among them.

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⁷ For this issue, Kim and Nelson (1999) will be very helpful.

References

- Alizadeh, A and N. Nomikos (2009) *Shipping Derivatives and Risk Management*, Palgrave Macmillan.
- Chen, S., H. Meersman and E. Voorde (2010) Dynamic Interrelationships in Returns and Volatilities between Capesize and Panamax Markets. *Maritime Economics & Logistics* 12, pp.65-90.
- Chung, K. J. and Y. Ha (2010a) The Empirical Analysis for the Effect of Global Finance-Crisis to the Baltic Dry Index, *Journal of Shipping and Logistics* Vol. 64, pp.1-16.
 - (2010b) The Structural Change in the BDI Function due to the Global Financial Crisis: Using the Kalman Filter, *Journal of Shipping and Logistics* Vol. 65, pp.217-231.
- Geweke, J. (1977) The Dynamic Factor Analysis of Economic Time Series. in *Latent Variables in Socio-Economic Models*, Aigner, D. and A. Goldberger (eds), North-Holland.
- Kim, C., and C. Nelson (1999) State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications, The MIT Press.
- Ko, Byoung-wook (2010a) A Mixed-Regime Model for Dry Bulk Freight Market, *The Asian Journal of Shipping and Logistics* Vol. 26 No. 2.

(2010b) A Study on the Change of the Dynamics of Dry Bulk Market before and after the 2008 Global Financial Crisis – applying the counterfactual analysis to VAR model, *Ocean Policy Research* Vol. 25 No. 2, Korea Maritime Institute.

- Macho, F., A. C. Harvey and J. H. Stock (1987) Forecasting and Interpolation Using Vector Autoregressions with Common Trends. *Annales d'Economie et de Statistique* No. 6/7, pp.279-287.
- Pesaran, M. H., H. Y. Shin, and R. Smith (2001) Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics* 16, pp.289-326.
- Rim, J., W. Kim and B. Ko (2010) An Empirical Analysis of the Dry Bulk Market Using a Recursive VAR Model. *Journal of Shipping and Logistics* Vol. 64, pp.17-35.
- Sargent, T. J. and C. A. Sims (1977) Business Cycle Modeling without Pretending to Have Too Much a Prior Economic Theory in *New Methods in Business Cycle Research*, Sims, C. A. *et al.* (eds), Federal Reserve Bank of Minneapolis.
- Stock, J. H and M. W. Watson (2008) forecasting in dynamic factor models subject to structural instability in *The Methodology and Practice of Econometrics, A Festschrift in Honour of Professor David F. Hendry*, Jennifer Castle and Neil Shephard (eds), Oxford: Oxford University Press.

(2006) Forecasting with Many Predictors. in *Handbook* of *Economic Forecasting*, Vol. 1, Elliot, G. et al (eds), North-Holland, pp.515-554.

(2005) Implications of Dynamic Factor Models for VAR Analysis, NBER Working Paper No. 11467.

(1991) A Probability Model of the Coincident Economic Indicators. *In Leading Economic Indicators: New Approaches and Forecasting Records*, ed. K. Lahiri and G. H. Moore, Cambridge University Press, pp.63-89.

The Baltic Exchange (2010) *A History of the Baltic Indices*, Baltic Exchange Information Services Ltd.

http://www.clarkson.net