AN INVESTIGATION INTO THE CORRECT SPECIFICATION FOR VOLATILITY IN THE SHIPPING FREIGHT RATE MARKETS

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Abstract

The research aim has been to further investigate the structure of freight rate volatility. This paper examines the use of the FIGARCH, as well as other GARCH-type models, namely the standard GARCH and the IGARCH models. The best model was then selected on the basis of their Value-at-Risk. The models were estimated and then tested using weekly spot freight rate data, between 6 January 1989 and 29 December 2006, for VLCC, Suezmax and Aframax tankers, as well as for Capesize and Panamax bulk-carriers.

Keywords: Shipping, GARCH-type models, Value-at-Risk, freight rates.
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1 INTRODUCTION

The aim of the research is to expand on the traditional models of freight rate volatility through the use of FI-GARCH models, and to propose finalisation on the debate regarding the structure of freight rate volatility, a crucial issue in the shipping industry, since if one can accurately forecast this, then one is effectively minimising risk exposure.

In addition, it is worth considering this methodology in other markets as well as shipping freight rate markets (perhaps the only financial market in which the good being provided is a service), as the modelling of freight rate volatility can be readily applied to other markets in which real assets are traded. In the shipping market, freight rates play a pivotal role, and form the basis of almost every function, from the determination of the price of the transport service through to the price of second-hand vessels. Therefore, a correct model for freight rate volatility is vital for all participants in the shipping market, from the ship-owners and charterers themselves, right down to ship-brokers, maritime lawyers and other auxiliary parties. This follows because, by reducing the risk exposure of the ship owners, one is passing that risk reduction down the line to the ancillary parties concerned.

Therefore, any model that can accurately forecast freight dynamics and volatility, and then the transition between periods of increasing and decreasing dynamics and volatility, will be of significant value.

We argue that freight rates are not non-stationary. The rationale behind this statement is that, although the demand for shipping services is inelastic, if freight rates reach really high levels then substitutes, such as air transport, become more attractive and charterers will take advantage of these. On the reverse side, if freight rates fall too low, then ship operators will either lay-up or scrap their vessels and seek their fortunes in other markets. We are further of the view that freight rates are also not stationary as there is a delay between the ordering and delivery of new vessels. As a result of this delay, the maximum supply of shipping services is fixed in the short-run and therefore prices may rise beyond the upper level indicated by a stationary process.

We investigate further whether freight rates and second-hand prices follow a process that falls somewhere between the non-stationary and stationary process, i.e. they are fractionally integrated. For this reason, when looking at the issue of volatility, establishing long memory models, such as the Fractionally Integrated Generalised Autoregressive Conditional Heteroscedasticity (FI-GARCH) models, would be more appropriate.

In a review of the literature, traditional fundamentals models have suggested that freight rates are mean reverting (Hawdon (1978) and Beenstock and Vergottis (1989)). However, research in the 1990s (Berg-Andereassen (1996); Glen (1997) and Kavussanos and Nomikos (2003), et al) found that freight rates were not mean reverting but followed a random walk process, and therefore were non-stationary in levels. In contradistinction, the most recent research (Adland and Cullinane (2006) and Koekebakker, Adland and Sodal (2006)) propose that the original fundamentals models of Hawdon and Beenstock and Vergottis were in fact correct and that freight rates are stationary, and that contrary conclusions were as a result of the application of an incorrect test. We put forward, for the first time in a market in which real assets are traded, the proposal that the answer may in fact lie somewhere between the two rival conclusions, i.e. that freight rates are fractionally integrated. This makes sense as any diagram of freight rates over time will illustrate that the process looks to be mean reverting. However, as recent events have shown, the process is still capable of 'exploding'. In addition, there is a delay between the ordering and delivery of new vessels, where this would entail that although freight rates are mean-reverting in the long-run, the mean reversion process would occur with a lag. This is in essence the definition of a long memory, or fractionally integrated process. In order to distinguish between types of volatility models, we used the traditional approach of measuring the Value-at-Risk for each model, and then comparing the accuracy of these forecasts.

Once again, if this hypothesis is true, it enables market participants to better forecast freight rate volatility, which in turn can lead to increased profits for market participants due to better investment-making capability and greater risk reduction. This can also have run-on effects on other markets, as most of the commodities traded in the world are transported by good. A better understanding of the transport costs involved enables charterers to better forecasts their costs and potentially pass on these cost-savings to other participants in other markets. Better forecasting of freight rates enables a better understanding of investment timing, which could then be applied to other markets in which real assets are traded. In addition to this, there are of course policy and decision making implications.

In order to provide body to the hypotheses, section three of this document presents the methodologies applicable to the research question. Section four of the document presents the data as well as descriptive statistics. Section five examines the implementation of FI-GARCH models in the shipping markets and section six provides a conclusion.

2 METHODOLOGY

Engle (1982) provided the framework for the variety of ARCH-type models presented here through the development of the original ARCH model. This framework was extended by Bollerslev (1986) who presented the standard GARCH (p; q) model used in this paper, which is represented as follows:

$$\varepsilon_t = z_t \sqrt{h_t} \;\; ; \;\; z_t \sim N \;\; 0; \; 1 \tag{2.1}$$

$$h_t = \omega + \alpha \;\; L \;\; \varepsilon_t^2 + \beta \;\; L \;\; h_t \tag{2.2}$$

In this model, L denotes the lag operator, hence $\alpha\ L \equiv \alpha_1 L + \alpha_2 L^2 + \ldots \alpha_q L^q$ and $\beta\ L = \beta_1 L + \beta_2 L^2 + \ldots \beta_p L^p$. In order to ensure the stability and covariance of the ε_t process, all the roots of $\left[1 - \alpha\ L - \beta\ L\right]$ and $\left[1 - \beta\ L\right]$ are constrained to lie outside the unit circle. One should note that in a GARCH (1; 1) model, the sum of α_1 and β_1 reflects the persistence of any shocks to volatility (Baillie, Bollerslev and Mikkelsen (1996)). This model enables one to generate volatility forecasts which are comprised of the weighted average of the constant long-run, or average, variance, denoted ω, the previous forecasting variance, denoted h_t, and the previous volatility reflecting the squared news about the return, denoted ε_t^2 (Kang, Kang and Yoon (2009)). This model could alternatively be expressed as an ARMA ($m; p$) process in ε_t^2, where:

$$\left[1 - \alpha\ L - \beta\ L\right]\varepsilon_t^2 = \omega + \left[1 - \beta\ L\right]v_t \tag{2.3}$$

In the expression above $m \equiv \max\ p; q$ and $v_t \equiv \varepsilon_1^2 - h_t$ is mean zero serially uncorrelated; thus, the v_t process may be readily interpreted as the 'innovations' for the conditional variance.

The IGARCH model, developed by Engle and Bollerslev (1986), is an extension of the GARCH (1;1) in that instead of the squared innovations of the current conditional variance decaying exponentially, or in other words stating that shocks in volatility persist for a relatively short period, as is the case of the GARCH model, these shocks are believed never to die out, i.e. it is characterised by infinite memory. The IGARCH model may be represented as follows:

$$\phi\ L\ \ 1 - L\ \ \varepsilon_t^2 = \omega + \left[1 - \beta\ L\right]v_t \tag{2.4}$$

$$h_t = \omega\left[1 - \beta\ L\right]^{-1} + 1 - \left[1 - \beta\ L\right]^{-1}\phi\ L\ \ 1 - L\ \ \varepsilon_t^2 \tag{2.5}$$

In the expression above $\phi\ L \equiv \left[1 - \alpha\ L - \beta\ L\right]\ 1 - L^{-1}$ is of order $m - 1$, In addition, the autoregressive lag polynomial, $1 - \alpha\ L - \beta\ L$, contains a unit root and all the roots of $\phi\ L$ and $\left[1 - \beta\ L\right]$ lie outside the unit root circle.

The final extension to the ARCH model examined here is the FIGARCH model proposed by Baillie, Bollerslev and Mikkelsen (1996). This is simply obtained by replacing the first difference operator in expression (2.5) with the fractional difference operator, denoted d, where $0 < d < 1$, hence:

$$\phi\ L\ \ 1 - L^{\ d}\ \varepsilon_t^2 = \omega + \left[1 - \beta\ L\right]v_t \tag{2.6}$$

$$h_t = \omega\left[1 - \beta\ L\right]^{-1} + 1 - \left[1 - \beta\ L\right]^{-1}\phi\ L\ \ 1 - L^{\ d}\ \ \varepsilon_t^2 \tag{2.7}$$

Once again, the autoregressive lag polynomial, $1-\alpha\ L\ -\beta\ L$, contains a unit root and all the roots of $\phi\ L$ and $\left[1-\beta\ L\ \right]$ lie outside the unit root circle. The argument behind the utilisation of this model is that the squared innovations of the current conditional variance would have a slow hyperbolic rate of decay. This would mean that shocks to volatility would persist longer than in the case of the GARCH model, but would eventually decay, unlike in the IGARCH model, hence the term long memory.

3 DESCRIPTION OF DATA

The aim of this section is to present the data that will be used to analyse the volatility of freight rates. This data was collected from Clarkson Shipping Intelligence Network, a database of all relevant data series for the shipping industry. In order to model the volatility of freight rates, prevailing weekly spot rates on shipping routes for five different types of vessels were selected (the details for the specific routes can be found in Footnote 1 of Table 3.01) and the returns on the spot rates were calculated as follows:

$$r_t = \ln\ FR_t\ - \ln\ FR_{t-1} \tag{3.8}$$

Where: FR_t is the prevailing spot freight rate on that route.

The sample period extending from 6 January 1989 to 28 December 2007 and thus consisted of 990 observations. Of the five types of vessels, three tankers, name VLCC, Suezmax and Aframax tankers, and two types of dry bulk vessels, i.e. Capesize and Panamax, were selected in order to give a balanced perspective of the tramp shipping market. Figures 4.01 and 4.02 illustrate these spot freight rates for the tankers and dry bulk vessels respectively, while Table 3.01 presents the descriptive statistics for the returns.

[INSERT FIGURE 3.01 ABOUT HERE]

[INSERT FIGURE 3.02 ABOUT HERE]

[INSERT TABLE 3.01 ABOUT HERE]

In the case of the tanker data series, the mean annualised returns are calculated to be 5.8%, 5.7% and 3.5% with respective annualised standard deviations of 79.5%, 78.5% and 74.3% for the VLCC, Suezmax and Aframax vessels, respectively. In all three cases, returns are found to be slightly positively skewed and exhibit large excess kurtosis, with the Jarque-Bera statistics indicating that we could reject the null hypothesis of normality for all three series. The Ljung-Box Q-statistics for the three data series indicate the presence of significant serial correlation at both the first and twelfth lags for the VLCC data series and at the twelfth lags for the Suezmax and Aframax data series; however, there is no evidence of significant serial correlation at the first lags for the Suezmax and Aframax data series. Finally, the ARCH tests indicate the presence of significant ARCH effects for all three data series at the first and twelfth lags, thus indicating that volatility would be well modelled by one of the ARCH family of models.

For the dry bulk vessels the annualised mean returns are 9.7% and 8.9%, with annualised standard deviations of 34.7% and 37% for the Capesize and Panamax data series, respectively. The Capesize returns illustrate slight positive skewness, whereas the returns for the Panamax data series are symmetrical, however both data series exhibit large excess kurtosis and the respective Jarque-Bera statistics illustrate that the null of normality can be rejected at all conventional levels of significance. Finally, we find that the presence of significant autocorrelation and ARCH effects for both data series at the first and twelfth lags, where the presence of significant ARCH effects indicate that volatility both data series would, as is the case for the tanker data series, be well modelled by one of the ARCH family of models.

4 EMPIRICAL RESULTS

4.1 Empirical Results for the GARCH-Class Models

Having run the GARCH (1; 0; 1), IGARCH (1; 1; 0) and FIGARCH (1; *d*; 0) models, the results of which can be found in Table 4.01, all three models come up with the similar results for the conditional mean, the lagged conditional mean and the levels of skewness and kurtosis. The coefficient for the conditional mean, μ_t, was found to range between 0.001 and 0.004 across data series, however, these values were insignificant, at all conventional levels of significance, across all data series. When examining the results for the conditional lagged mean, μ_{t-1}, these were found to be negative and significant at all conventional levels of significance for the VLCC, Capesize and Panamax data series; while the values for the Suezmax and Aframax series, while still negative, were insignificant at all conventional levels, except in the case of the IGARCH model for the Suezmax data series, where this figure was significant at the 5% and 10% levels of significance. Finally, all data series and models indicated the presence of slight positive skewness and excess kurtosis, where these were significant at all conventional levels of significance. The exception here is the case of the Panamax data series, where the GARCH model, results indicate that the skewness was only significant at the 10% level of significance, and the IGARCH and FIGARCH model results indicate that the skewness is only significant at the 5% and 10% levels of significance.

[INSERT TABLE 4.01 ABOUT HERE]

Where the empirical results start to differ across models is in the estimation of the GARCH-type parameters. The coefficients for the constant long-run variance, ω, were insignificant, at all conventional levels of significance, across all data series in the case of the GARCH and FIGARCH models, and for the Suezmax, Capesize and Panamax data series for the IGARCH models, however, they were effectively zero and significant at all conventional levels of significance. The coefficients for β_1, which measures the impact of past shocks on the level of volatility, differed across the data series and models. For the VLCC, Suezmax and Panamax data series for the GARCH model, this parameter was found to range between 0.891 and 0.974, with these values being significant at all conventional levels of significance, whereas the

coefficients for the Aframax and Capesize data series were found to be insignificant at all conventional levels of significance. In the case of the IGARCH model, coefficients ranged between 0.715 and 0.975, where these results were all significant at all conventional levels of significance. Finally, in the case of the FIGARCH model, coefficients for the data series were found to insignificant at all conventional levels of significance, with the exception of the VLCC data series, where the coefficient is 0.5, and significant at all conventional levels. Results for the coefficient for ϕ_1, where this measures the level of persistence in volatility, differ somewhat for the GARCH model in that although all are significant at all conventional levels of significance, the VLCC, Suezmax and Panamax data series all exhibit extreme persistence in volatility, with values of 0.999 for the VLCC and Suezmax data series and 0.946 for the Panamax data, while the results for the Aframax and Capesize data illustrate some persistence, with coefficients of 0.622 and 0.818, respectively. This parameter, which is the sum of the α_1 and β_1 parameters, is not calculated for the IGARCH and FIGARCH models as there is no α_1 parameter for these models, thus persistence in these cases is measured by the β_1 parameter.

The final parameter to discuss is *d*, which is indicates the level of fractional integration for the data series, where this is only estimated for the FIGARCH model, as the GARCH model inherently assumes that the data series follows an I(0) process, while the IGARCH model implies that volatility is an I(1) process. All five data series have coefficients for *d* which are significant at all conventional levels, and which range between 0.157 and 0.49.

Having run the models, we once again tested the models to determine whether any autocorrelation and ARCH effects had been removed. In terms of the presence of autocorrelation, the tests revealed that for the GARCH model, all five data series still had significant autocorrelation, at all conventional lags at the 20th lag; whereas for the IGARCH model, the Suezmax and Aframax data series had significant autocorrelation at all conventional levels at the 20th lag, whereas the VLCC data series had persistent autocorrelation at the 20th lag for the IGARCH and FIGARCH models, however, this was only significant at the 5% and 10% levels for the IGARCH model and the 10% level for the FIGARCH model. The test for ARCH effects indicated that there are no significant ARCH effects at the 20th lag for any model and any data series.

A point of interest is that for all data series, except for the Capesize data series, the level of skewness increased between the GARCH and FIGARCH models, which may suggest that the FIGARCH model may be capturing more of the dynamics of the series in these cases. In addition, the level of kurtosis decreased all cases, except for the Panamax data series, which may indicate that the problem of fat tails is reduced. Finally, the log-likelihood estimation indicates that the FIGARCH model is preferred in all cases, except in the case of the Panamax data series, where the GARCH and FIGARCH models have the same log-likelihood value. For these reasons, and the fact that the FIGARCH model removed the most autocorrelation and all the ARCH effects, we can conclude that the FIGARCH model may present the best GARCH-type model for freight rate volatility.

4.2 An Examination of the Values-at-Risk

Having estimated the respective GARCH, IGARCH and FIGARCH models, we re-estimated the models using a smaller in-sample period, which extended from 6 January 1989 to 29 March 2002, and using these estimates performed a one-day ahead rolling volatility forecast, with the out-of-sample period extending from 5 April 2002 to 28 December 2007. The aim of this forecast was to ultimately calculate the respective 1% and 5% Values-at-Risk (VaR) for all models across all data series.

One should note that should a VaR for a model be higher than the actual VaR incurred, this would mean too much capital has have been kept in reserve as security to cover potential losses, where this could have better utilised for investment decisions elsewhere. However, if the VaR for a model is lower than the actual VaR, this would mean that the actual losses exceeded the forecast levels, and the relevant parties would have not kept enough capital in reserve and thus may have not been able to cover actual losses.

[INSERT TABLE 4.02 ABOUT HERE]

The VaR figures are presented in Table 4.02 and illustrate some interesting, but somewhat mixed, results. If one was to compare the 1% and 5% VaR figures for the three model against each other, one would find that in the case of the VLCC, Aframax and Capesize data series, the GARCH model provides the lowest variable, whereas for the Suezmax data series that would apply to the FIGARCH model and for the Panamax data series, the IGARCH model. One should note, however, that the GARCH model for the Aframax data series was illustrated in Table 4.01 to have failed to remove all present ARCH effects, and therefore we can conclude that in that case the most appropriate model may in fact be the FIGARCH model. The same applies if you were to compare each model's 1% and 5% VaR to the actual VaR for the data series, i.e. the VaR calculated on the historic data as opposed to the respective forecasts. We feel that these results may indicate that there is some form of size effect with respect to the volatility of tankers and bulk carriers as the smaller-size vessels in each case illustrated more persistence in volatility.

An important element to note is that, as we have stated earlier, the fact that the 1% and 5% VaR for the actual data series is lower than that for any of the respective models means that the forecast estimates all erred on the conservative side. For this reason, we specified the best model as the model which has the least negative VaR, or the VaR which is closest to the actual VaR.

5 CONCLUSION

This paper examined for the first time in the shipping literature the issue of fractional integration in freight rate volatility. In order to do this, we estimated three models, namely standard GARCH (Bollerslev (1986)), IGARCH (Engle and Bollerslev (1986)) and FIGARCH (Baillie, Bollerslev and Mikkelsen (1996)) models. The rationale behind this research was that there is a delay between the ordering and delivery of new vessels, where this would entail that, although freight rates are

mean-reverting in the long-run, the mean reversion process would occur with a lag. This is in essence the definition of a long memory, or fractionally integrated process.

Based on the estimates of each of these models, we find that the most appropriate model, based on the respective log-likelihoods, was the FIGARCH model in all cases. In order to provide a practical, rather than purely statistical basis for our model selection, we subsequently performed a one-day rolling forecast using a sub-sample of the data for our out-of-sample analysis, calculated the VaR for each of the models, and then compared these with the actual VaR for each of the data series. We find that for the VLCC and Capesize data series, the most appropriate model was the GARCH model, whereas, for the Suezmax and Aframax data series, the most appropriate model was found to be the FIGARCH model and the best model for the Panamax data series was the IGARCH model. We feel that these results once again may indicate that there is some form of size effect for the volatility of tankers and bulk carriers as the smaller-size vessels in each case illustrated more persistence in volatility.

To conclude, we feel that although these results do provide some clarity and insight as to the structure of freight rate volatility in the shipping markets, the fact that the results are somewhat mixed may indicate a need for further examination and reflection as to other potential types of models that may possibly be more accurately employed..

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Figure 3.01 – Spot Freight Rates for Tankers (6 January 1989 to 28 December 2007)

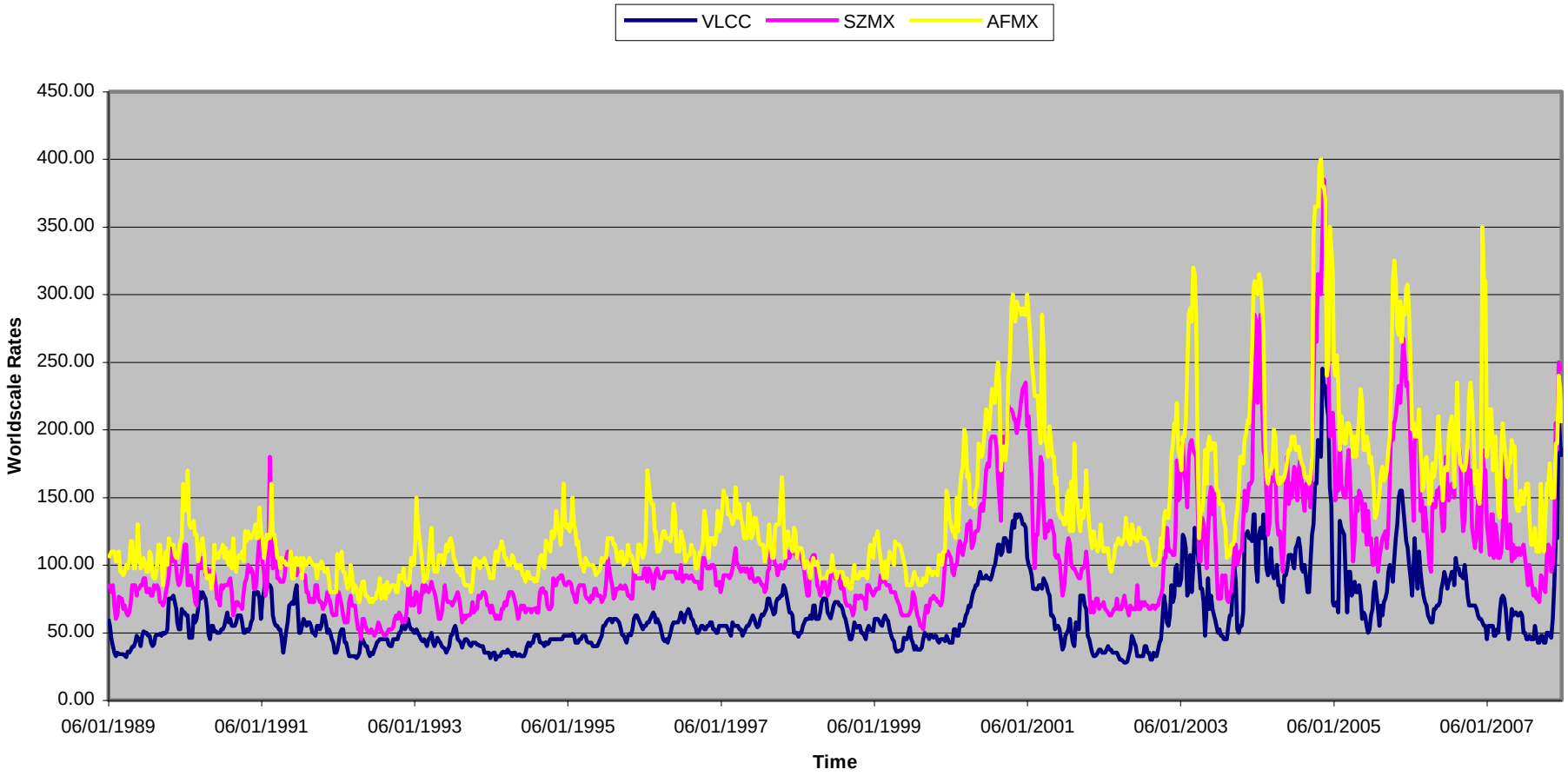

Figure 3.02 – Spot Freight Rates for Bulk Carriers (6 January 1989 to 28 December 2007)

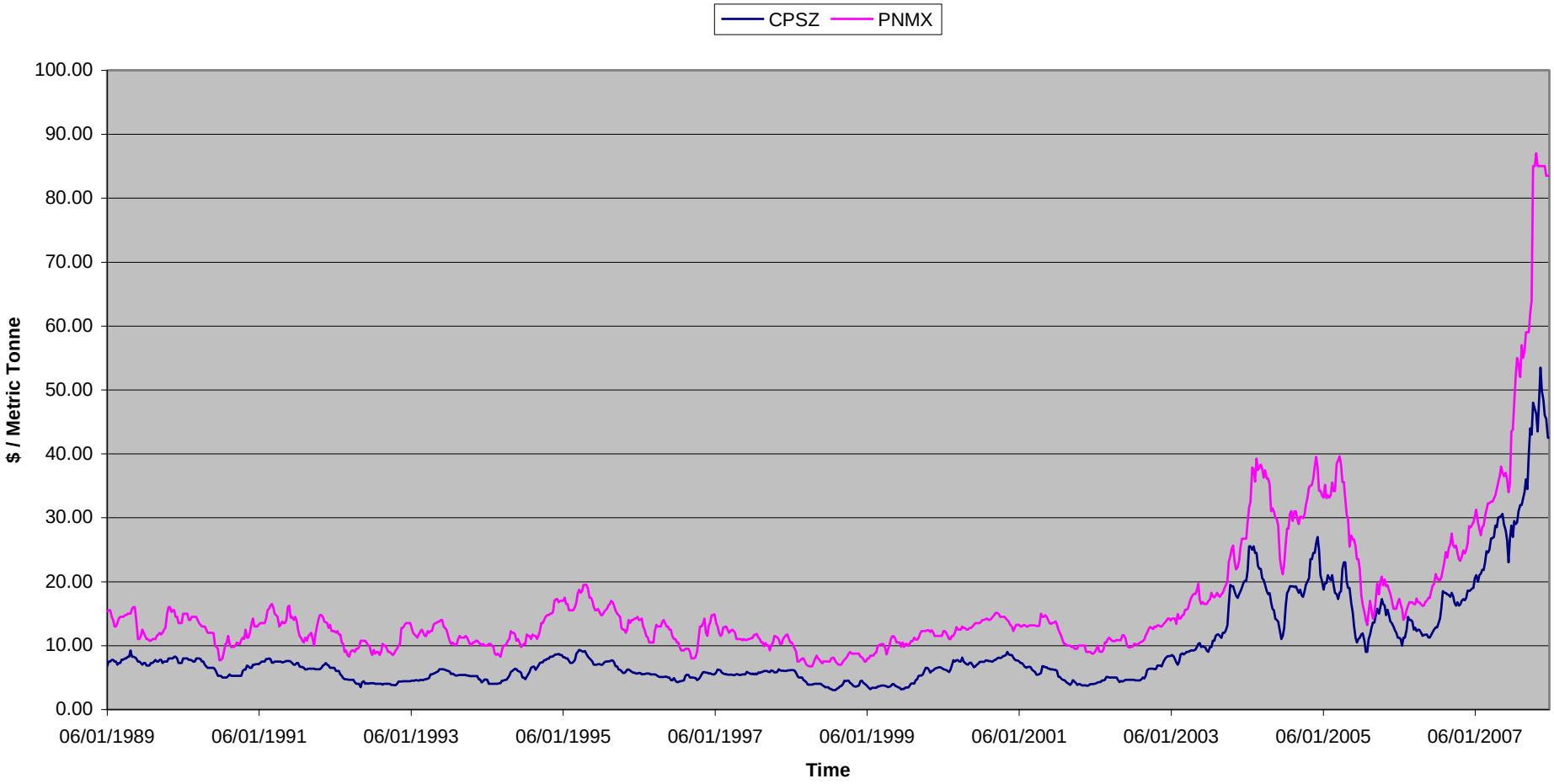

Table 3.01 – Descriptive Statistics for Spot Freight Rate Returns

	VLCC	SZMX	AFMX	CPSZ	PNMX
Sample Size	991.000	991.000	991.000	991.000	991.000
Mean	0.058	0.057	0.035	0.097	0.089
Variance	0.633	0.616	0.552	0.121	0.137
Std. Dev.	0.795	0.785	0.743	0.347	0.370
Skewness	0.436	0.539	0.512	0.495	0.134
Kurtosis	9.375	5.685	9.104	5.885	6.234
Jarque-Bera	1707.699	345.444	1580.408	383.652	434.316
Probability	0.000	0.000	0.000	0.000	0.000
Q(1)	11.602	1.850	1.103	73.064	48.983
Probability	0.001	0.174	0.294	0.000	0.000
Q(12)	61.579	53.077	60.103	92.602	64.282
Probability	0.000	0.000	0.000	0.000	0.000
ARCH(1)	4.395	24.651	7.108	40.072	6.505
Probability	0.036	0.000	0.008	0.000	0.011
ARCH(12)	201.600	126.630	49.058	76.988	26.000
Probability	0.000	0.000	0.000	0.000	0.011

Note 1: VLCC denotes the weekly spot freight rate returns for a 270,000 DWT VLCC tanker carrying crude oil from Ras Tanura (Saudi Arabia) to Rotterdam (Netherlands).
SZMX denotes the weekly spot freight rate returns for a 130,000 DWT Suezmax tanker carrying crude oil from Bonny (Nigeria) to off the coast of Philadelphia (USA).
AFMX denotes the weekly spot freight rate returns for an 80,000 DWT Aframax tanker carrying crude oil from Sullom Voe (UK) to Bayway (USA).
CPSZ denotes the weekly spot freight rate returns for a 145,000 DWT Capesize bulk-carrier carrying iron ore from Tubarao (Brazil) to Rotterdam (Netherlands).
PNMX denotes the weekly spot freight rate returns for a 55,000 DWT Panamax bulk-carrier carrying grain from the US-Gulf (USA) to Rotterdam (Netherlands).

Note 2: The sample period for the data used for this table extends from 13 January 1989 to 28 December 2006, with a total of 990 observations.

Note 3: The spot freight rates for the VLCC, Suezmax and Aframax tankers' data series are denoted in Worldscale units.

Note 4: The spot freight rates for the Capesize and Panamax bulk-carriers' data series are denoted in US$ per metric tonne.

Note 5: The data used for this table is all sourced from the Clarkson Shipping Intelligence Network (www.clarskons.net).

Table 4.01 – Results from the GARCH-Type Models for Freight Rate Returns

	GARCH (1; 0; 1)					IGARCH (1; 1; 0)					FIGARCH (1; *d*; 0)				
	VLCC	SZMX	AFMX	CPSZ	PNMX	VLCC	SZMX	AFMX	CPSZ	PNMX	VLCC	SZMX	AFMX	CPSZ	PNMX
μ	0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.002	0.001	0.001	0.003	0.004	0.002	0.001	0.001
	(0.282)	(0.413)	(0.681)	(0.505)	(0.259)	(0.327)	(0.424)	(0.521)	(0.511)	(0.305)	(0.290)	(0.112)	(0.507)	(0.671)	(0.355)
$\mu_{1-\tau-}$	**-0.149**	-0.063	-0.002	**-0.305**	**-0.237**	**-0.149**	-0.063	0.026	**-0.298**	**-0.225**	**-0.141**	-0.049	0.019	**-0.300**	**-0.238**
	(0.000)	(0.131)	(0.949)	**(0.000)**	**(0.000)**	**(0.000)**	(0.030)	(0.439)	**(0.000)**	**(0.000)**	**(0.000)**	(0.173)	(0.578)	**(0.000)**	**(0.000)**
ω	0.000	0.000	0.004	0.000	0.000	**0.000**	0.000	**0.001**	0.000	0.000	0.000	0.000	0.001	0.000	0.000
	(0.469)	(0.451)	(0.111)	(0.254)	(0.346)	**(0.000)**	(0.223)	**(0.000)**	(0.359)	(0.442)	(0.360)	(0.588)	(0.297)	(0.581)	(0.999)
β_1	**0.934**	**0.974**	0.430	0.617	**0.891**	**0.934**	**0.975**	**0.715**	**0.820**	**0.975**	**0.500**	0.067	0.000	0.000	0.067
	(0.000)	**(0.000)**	(0.179)	(0.014)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.292)	(0.999)	(1.000)	(0.218)
ϕ_1	**0.999**	**0.999**	**0.622**	**0.818**	**0.946**	---	---	---	---	---	---	---	---	---	---
	(0.000)	**(0.000)**	**(0.003)**	**(0.000)**	**(0.000)**	(---)	(---)	(---)	(---)	(---)	(---)	(---)	(---)	(---)	(---)
d	---	---	---	---	---	---	---	---	---	---	**0.490**	**0.267**	**0.166**	**0.202**	**0.157**
	(---)	(---)	(---)	(---)	(---)	(---)	(---)	(---)	(---)	(---)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
log L	931	873	872	1678	1578	931	873	854	1669	1571	935	877	878	1681	1578
b_3	**0.435**	**0.541**	**0.514**	**0.495**	0.135	**0.311**	**0.698**	**1.125**	**0.349**	0.163	**0.327**	**0.694**	**0.893**	**0.373**	0.167
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	(0.083)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.037)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.032)
b_4	**9.414**	**5.701**	**9.133**	**5.938**	**6.251**	**5.268**	**5.399**	**10.958**	**5.607**	**6.665**	**5.030**	**5.059**	**6.057**	**2.496**	**6.511**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Q (20)	**56.907**	**63.180**	**81.216**	**81.151**	**66.704**	32.648	**56.177**	**71.121**	13.336	14.456	30.178	**56.564**	**79.125**	13.765	12.827
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.037)	**(0.000)**	**(0.000)**	(0.863)	(0.807)	(0.067)	**(0.000)**	**(0.000)**	(0.842)	(0.885)
Q^2(20)	19.766	18.518	37.285	15.884	20.103	17.768	24.748	18.723	16.196	22.813	11.915	19.513	19.251	10.966	20.280
	(0.473)	(0.553)	(0.011)	(0.724)	(0.452)	(0.603)	(0.211)	(0.540)	(0.704)	(0.298)	(0.919)	(0.489)	(0.506)	(0.947)	(0.441)

Note 1: See notes from Table 3.01.
Note 2: Figures in parentheses are the respective *p*-values, while figures in bold are significant at all conventional levels of significance.

Table 4.02 – Estimated Values-at-Risk for the Data Series

GARCH (1;0;1)	VLCC	SZMX	AFMX	CPSZ	PNMX
VAR01	-$334,271.18	-$310,932.65	-$237,810.86	-$118,392.85	-$114,062.80
VAR05	-$236,404.17	-$219,898.63	-$168,185.24	-$83,730.11	-$80,667.80

IGARCH (1;1;0)	VLCC	SZMX	AFMX	CPSZ	PNMX
VAR01	-$344,694.83	-$329,773.72	-$286,746.25	-$139,139.09	-$105,073.95
VAR05	-$243,776.01	-$233,223.46	-$202,793.46	-$98,402.33	-$74,310.68

FIGARCH (1;d;0)	VLCC	SZMX	AFMX	CPSZ	PNMX
VAR01	-$336,155.84	-$301,902.38	-$262,048.90	-$121,699.21	-$112,554.85
VAR05	-$237,737.04	-$213,512.22	-$185,326.93	-$86,068.44	-$79,601.35

ACTUAL	VLCC	SZMX	AFMX	CPSZ	PNMX
VAR01	-$252,922.90	-$265,654.81	-$190,474.07	-$87,787.31	-$80,115.24
VAR05	-$178,872.82	-$187,877.12	-$134,707.59	-$62,085.18	-$56,659.32

Note 1: See notes from Table 3.01.
Note 2: VAR01 denotes the 1% Value-at-Risk, while VAR05 denotes the 5% Value-at-Risk
Note 3: Actual denotes the Values-at-Risk for the actual data series as opposed to forecasts.
Note 4: These Value-at-Risk figures are based on an initial capitalisation level of US$1 million.