Constant vs. time-varying hedge ratios and hedging efficiency in the BIFFEX market

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Abstract

This paper estimates time-varying and constant hedge ratios, and investigates their performance in reducing freight rate risk in routes 1 and 1A of the Baltic Freight Index. Time-varying hedge ratios are generated by a bivariate error correction model with a GARCH error structure. We also introduce an augmented GARCH (GARCH-X) model where the error correction term enters in the specification of the conditional covariance matrix. This specification links the concept of disequilibrium (as proxied by the magnitude of the error correction term) with that of uncertainty (as reflected in the time varying second moments of spot and futures prices). In- and out-of-sample tests reveal that the GARCH-X specification provides greater risk reduction than a simple GARCH and a constant hedge ratio. However, it fails to eliminate the riskiness of the spot position to the extent evidenced in other markets in the literature. This is thought to be the result of the heterogeneous composition of the underlying index. It seems that restructuring the composition of the Baltic Freight Index (BFI) so as to reflect homogeneous shipping routes may increase the hedging effectiveness of the futures contract. This by itself indicates that the imminent introduction of the Baltic Panamax Index (BPI) as the underlying asset of the Baltic International Financial Futures Exchange (BIFFEX) contract is likely to have a beneficial impact on the market. © 2000 Elsevier Science Ltd. All rights reserved.

1. Introduction

The Baltic International Financial Futures Exchange (BIFFEX) contract was introduced in 1985 as a mechanism for hedging freight rate risk in the dry-bulk sector of the shipping industry. On the basis of their exposure to the risk of adverse movements in freight rates, market agents can
sell or buy futures contracts representing the expected future value of the Baltic Freight Index (BFI), a weighted average dry-cargo freight rate index. The index is compiled from actual spot and time-charter freight rates on 11 component routes on which two distinct categories of vessels operate; panamax vessels (vessels with a carrying capacity between 52,000 and 70,000 tons, used primarily to carry grain from North America and Argentina, and coal from North America and Australia) which make up 70% of the index composition, and capesize vessels (between 100,000 and 150,000 tons, which transport iron ore mainly from Brazil, and coal from North America and Australia) which account for the remaining 30% (Table 1). ¹

Unlike other futures markets, in which futures contracts are used as a hedge against price fluctuations in the underlying asset, in the BIFFEX market futures contracts are employed as a cross-hedge against freight rate fluctuations on the individual shipping routes which constitute the BFI. The relationship between BFI and BIFFEX prices has been investigated in Kavussanos and Nomikos (1999). They find that futures prices one and two months from maturity provide unbiased forecasts of the realised spot prices suggesting that, for these maturities, hedgers in the market can use the futures contract efficiently without paying any risk premium. However, they also emphasise that the effectiveness of the hedging mechanism depends primarily on the relationship between BIFFEX prices and the shipping routes which constitute the BFI. This issue is analysed in the current study.

The objective of hedging is to control or reduce the risk of adverse price changes in the spot market. To achieve this, the hedger determines a hedge ratio, i.e. the number of futures contracts to buy or sell for each unit of spot commodity on which he bears price risk. It is important then for the hedger to select appropriate models that give reliable estimates of these ratios. This paper estimates alternative models that generate time-varying and constant hedge ratios, and selects the one that minimises freight rate risk in routes 1 and 1A of the BFI. This issue is of considerable

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¹ See Table 1 for this, and Section 3 of the paper for further discussion.
interest to those trading in the BIFFEX market. Market agents (shipowners or charterers) whose physical operations concentrate on these BFI routes can benefit from using optimal hedge ratios that control their freight rate exposure efficiently.

Earlier studies in the literature (Johnson, 1960; Stein, 1961; Ederington, 1979) derive hedge ratios that minimise the variance of price changes in the hedged portfolio based on the principles of portfolio theory. Let $\Delta S_t$ and $\Delta F_t$ represent changes in spot and futures prices between period $t$ and $t - 1$. Then the variance-minimising hedge ratio is the ratio of the unconditional covariance between cash and futures price changes to the variance of futures price changes; this is equivalent to the slope coefficient, $\gamma^*$, in the following regression:

$$\Delta S_t = \gamma_0 + \gamma^* \Delta F_t + u_t; \quad u_t \sim iid(0, \sigma^2).$$  \hspace{1cm} (1)

Within this specification, the higher the $R^2$ of Eq. (1) the greater the effectiveness of the minimum-variance hedge. Minimum risk hedge ratios and measures of hedging effectiveness are estimated for T-bill futures by Ederington (1979) and Franckle (1980), for the oil futures by Chen et al. (1987), for stock indices by Figlewski (1984) and Lindahl (1992), for currencies by Grammatikos and Saunders (1983) and by Malliaris and Urrutia (1991), and for the freight futures market by Thuong and Visscher (1990) and Haralambides (1992). The major conclusion of these studies is that commodity and financial futures contracts perform well as hedging vehicles with $R^2$s ranging from 0.80 to 0.99. In contrast, for the freight futures market, the $R^2$s vary from 0.32 to less than 0.01 across different shipping routes. This poor hedging performance of the BIFFEX contract is thought to be the result of the heterogeneous composition of the BFI in terms of dissimilar shipping routes, fixtures (spot and time-charter freight rates), vessel sizes and transported commodities.

This method of calculating hedge ratios is demonstrated by Myers and Thompson (1989) and Kroner and Sultan (1993) to have several weaknesses. The first objection is related to the implicit assumption in Eq. (1) that the risk in spot and futures markets is constant over time. This assumption contrasts sharply with the fact that many asset prices are characterised by time-varying distributions which implies that optimal, risk-minimising hedge ratios should be time-varying. A second problem is that Eq. (1) is potentially mispecified because it ignores the existence of a long-run cointegrating relationship between spot and futures prices (Engle and Granger, 1987). These issues raise concerns regarding the risk reduction properties of the hedge ratios generated from Eq. (1). While these problems have been addressed in several commodity and financial futures markets (see e.g., Kroner and Sultan, 1993; Gagnon and Lypny, 1995, 1997) there has been no empirical evidence for the BIFFEX market. This paper fills this gap in the literature.

We model the spot and futures returns as a vector error correction model (VECM) (Engle and Granger, 1987; Johansen, 1988) with a GARCH error structure (Bollerslev, 1986). This framework meets the earlier criticisms since the VECM models the long-run relationship between spot and futures prices and the GARCH error structure permits the second moments of their joint distribution to change over time; the time-varying hedge ratios are then calculated from the estimated covariance matrix of the model. We also extend previous research in other futures markets by including the squared lagged error correction term (ECT) of the cointegrated spot and futures prices in the specification of the conditional variance in what is termed the GARCH-X model (Lee, 1994). A principal feature of cointegrated variables is that their time paths are influenced by the extent of deviations from their long-run equilibrium (Engle and Granger, 1987).
As spot and futures prices respond to the magnitude of disequilibrium then, in the process of adjusting, they may become more volatile. If this is the case then the inclusion of the ECT in the conditional variance specification is appropriate and may lead to the estimation of more accurate hedge ratios.

This paper then contributes to the existing literature in a number of ways. First the effectiveness of constant and time-varying hedge ratios in the BIFFEX market is investigated for the first time. Second, we estimate different model specifications so as to arrive at the most appropriate model that produces the most effective ratio. Third, in- and out-of-sample tests are employed to assess the effectiveness of the futures contract. In the above, the selection criterion (loss function) for the optimum model to use is the variance reduction of the hedged portfolio.

The structure of this paper is as follows: the next two sections present the minimum-variance hedge ratio methodology and illustrate the empirical model that is used in this study; Section 4 provides some background on the BIFFEX market and discusses the properties of the data; Section 5 offers empirical results and Section 6 evaluates the hedging effectiveness of the proposed strategies. Finally, Section 7 concludes this study.

2. Hedging and time-varying hedge ratios

Market participants in futures markets choose a hedging strategy that reflects their individual goals and attitudes towards risk. In particular, consider the case of a shipowner who wants to secure his freight rate income in the freight futures market. The return on the shipowner’s portfolio of spot and futures positions can be denoted by

\[ R_{H,t} = R_{S,t} - \gamma_t R_{F,t}, \]

where \( R_{H,t} \) is the return on holding the portfolio between \( t - 1 \) and \( t \); \( R_{S,t} \) is the return on holding the spot position between \( t - 1 \) and \( t \), i.e. the freight rate revenue; \( R_{F,t} \) is the return on holding the futures position between \( t - 1 \) and \( t \); and \( \gamma_t \) is the hedge ratio, i.e. the number of futures contracts that the hedger must sell for each unit of spot commodity on which he bears price risk. The variance of the returns of the hedged portfolio, conditional on the information set available at time \( t - 1 \), is given by

\[
\text{Var}(R_{H,t} | \Omega_{t-1}) = \text{Var}(R_{S,t} | \Omega_{t-1}) - 2\gamma_t \text{Cov}(R_{S,t}, R_{F,t} | \Omega_{t-1}) + \gamma_t^2 \text{Var}(R_{F,t} | \Omega_{t-1}), \tag{2}
\]

where \( \text{Var}(R_{S,t} | \Omega_{t-1}), \text{Var}(R_{F,t} | \Omega_{t-1}) \) and \( \text{Cov}(R_{S,t}, R_{F,t} | \Omega_{t-1}) \) are, respectively, the conditional variances and covariance of the spot and futures returns. The optimal hedge ratio is defined as the value of \( \gamma_t \) which minimises the conditional variance of the hedged portfolio returns, i.e. \( \min[\text{Var}(R_{H,t} | \Omega_{t-1})] \). Taking the partial derivative of Eq. (2) with respect to \( \gamma_t \), setting it equal to zero and solving for \( \gamma_t \), yields the optimal hedge ratio conditional on the information available at \( t - 1 \), as follows (see e.g., Baillie and Myers, 1991)

\[
\gamma_t^* | \Omega_{t-1} = \frac{\text{Cov}(R_{S,t}, R_{F,t} | \Omega_{t-1})}{\text{Var}(R_{F,t} | \Omega_{t-1})}. \tag{3}
\]

If returns are defined as the logarithmic differences of spot and futures prices, then (3) can be expressed equivalently as
The conditional minimum-variance hedge ratio of Eq. (4) is the ratio of the conditional covariance of spot and futures price changes over the conditional variance of futures price changes. Moreover, the conditional hedge ratio nests the conventional hedge ratio, $\gamma_t^*$ in Eq. (1); if we replace the conditional moments in Eq. (2) by their unconditional counterparts and minimise with respect to $\gamma_t$ then we get the conventional hedge ratio. Because the conditional moments can change as new information arrives in the market and the information set is updated, the time-varying hedge ratios may provide superior risk reduction compared to static hedges.

3. Time-varying hedge ratios and ARCH models

To estimate $\gamma_t^*$ in Eq. (4), the conditional second moments of spot and futures prices are measured using the family of ARCH models, introduced by Engle (1982). For this purpose, we employ a VEC model for the conditional means of spot and futures returns with a GARCH error structure. The error correction part of the model is necessary because spot and futures prices share a common stochastic trend, and the GARCH error structure permits the variances and the covariance of the price series to be time-varying. Therefore, the conditional means of spot and futures returns are specified using the following VECM:

$$
\Delta X_t = \mu + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t; \quad \varepsilon_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} | \Omega_{t-1} \sim \text{distr}(0, H_t),
$$

where $X_t = (S_t, F_t)'$ is the vector of spot and futures prices, $\Gamma_i$ and $\Pi$ are $2 \times 2$ coefficient matrices measuring the short- and long-run adjustment of the system to changes in $X_t$ and $\varepsilon_t$ is the vector of residuals $(\varepsilon_{S,t}, \varepsilon_{F,t})'$ which follow an as-yet-unspecified conditional distribution with mean zero and time-varying covariance matrix, $H_t$.

The existence of a long-run relationship between spot and futures prices is investigated in the VECM of Eq. (5) through the $\lambda_{\max}$ and $\lambda_{\text{trace}}$ statistics (Johansen, 1988) which test for the rank of $\Pi$. If $\text{rank}(\Pi) = 0$, then $\Pi$ is the $2 \times 2$ zero matrix implying that there are no cointegrating relationships between $S_t$ and $F_t$; in this case, (5) is reduced to a VAR model in first differences. If $\text{rank}(\Pi) = 2$, then all the variables in $X_{t-1}$ are $I(0)$ and the appropriate strategy is to estimate a VAR model in levels. If $\text{rank}(\Pi) = 1$, then there is a single cointegrating vector and $\Pi$ can be factored as $\Pi = \alpha \beta'$, where $\alpha$ and $\beta'$ are $2 \times 1$ vectors. Using this factorisation, $\beta'$ represents the...
vector of cointegrating parameters and $z$ is the vector of error correction coefficients measuring the speed of convergence to the long run steady state. The significance of incorporating the cointegrating relationship into the statistical modelling of spot and futures prices is emphasised in studies such as Kroner and Sultan (1993), Ghosh (1993), Chou et al. (1996) and Lien (1996); hedge ratios and measures of hedging performance may change sharply when this relationship is unduly ignored from the model specification.

The conditional second moments of spot and futures returns are specified as a GARCH(1, 1) model (Bollerslev, 1986) using the following augmented Baba et al. (1987) (henceforth, BEKK) representation (see Engle and Kroner, 1995)

$$H_t = C'C + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B + D'W_{t-1}D,$$

where $C$ is a $2 \times 2$ lower triangular matrix, $A$ and $B$ are $2 \times 2$ diagonal coefficient matrices, with $x_{ii}^2 + \beta_{ii}^2 < 1$, $i = 1, 2$ for stationarity, $W_{t-1}$ represents additional explanatory variables which belong to $\Omega_{t-1}$ and influence $H_t$, and $D$ is a $1 \times 2$ vector of coefficients. In this diagonal representation, the conditional variances are a function of their own lagged values and their own lagged error terms, while the conditional covariance is a function of lagged covariances and lagged cross products of the $e'_t$s. Moreover, this formulation guarantees $H_t$ to be positive definite almost surely for all $t$ and, in contrast to the constant correlation model of Bollerslev (1990), it allows the conditional covariance of spot and futures returns to change signs over time.

Additional explanatory variables may be incorporated in $H_t$ through the $W_{t-1}$ term. Lee (1994) for instance, in the examination of spot and forward exchange rates, includes the square of the lagged error correction term (ECT). A similar specification is adopted by Choudhry (1997) in examining spot and futures stock indices returns. By including the squared lagged ECT term, $z_{t-1}^2 = (\beta'X_{t-1})^2$, in the conditional variance equation, one can examine the temporal relationship between disequilibrium, as proxied by the magnitude of the ECT, and uncertainty, which is measured by the time varying variances. If spot and futures prices deviate from their long-run relationship then they may become more volatile as they respond to eliminate these deviations. If this is the case, then the inclusion of the error correction term in the conditional variance may be appropriate.

Preliminary evidence on our data set with the conditional normal distribution reveals substantial excess kurtosis in the estimated standardised residuals even after accounting for second moment dependencies. As demonstrated in Bollerslev and Wooldridge (1992), this invalidates traditional inference procedures. Following Bollerslev (1987), the conditional Student-\(t\) distribution is used as the density function of the error term, $e_t$, and the degrees of freedom, $v$, is treated as another parameter to be estimated. The general form of the likelihood function becomes

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4 The $A$ and $B$ matrices are restricted to be diagonal because this results in a more parsimonious representation of the conditional variance; see as well Bollerslev et al. (1994). Moreover, a GARCH(1, 1) model is used because of the substantial empirical evidence that this model adequately characterises the dynamics in the second moments of spot and futures prices; see Kroner and Sultan (1993), Gagnon and Lypny (1995, 1997), Tong (1996) and Bera et al. (1997) for evidence on this.

5 For a discussion of the properties of this model and alternative multivariate representations of the conditional covariance matrix, see Bollerslev et al. (1994) and Engle and Kroner (1995).
\[ L(\varepsilon_t, H_t) = \frac{\Gamma[(2 + v)/2]}{\Gamma(v/2)(\sqrt{\pi(v - 2)})^2} |H_t|^{-1/2} \left[ 1 + \frac{1}{v - 2} \varepsilon_t \mathcal{H}_t^{-1} \varepsilon_t \right]^{-(v+2)/2}, \quad v > 2, \]  

where \( \Gamma(\cdot) \) is the gamma function and \( v \) denotes the degrees of freedom. This distribution converges to the multivariate normal as \( v \to \infty \) although, in empirical applications, the two likelihood functions give similar results for values of \( v \) around 30.

4. Data and preliminary analysis

The data for this study consist of weekly spot and futures prices from 23 September 1992 to 31 October 1997. 6 The spot price data are Wednesday closing prices of the BFI Route 1 and Route 1A prices and the futures prices are Wednesday closing prices of the futures contract which is nearest to maturity. 7 In order to avoid the problems associated with thin markets and expiration effects, it is assumed that a hedger rolls over to the next nearest contract one week prior to the expiration of the current contract. Data are provided from London International Financial Futures Exchange (LIFFE) and are transformed into natural logarithms for analysis.

Cross-hedging freight rate risk using an average index based futures contract is only successful when the freight rate and the futures price behave similarly. Consider for instance Figs. 1 and 2 showing the futures (BIFFEX) and route 1 and route 1A index prices over the sample period examined; for comparison purposes we plot on the same graph the BFI prices. We can see that, although BIFFEX and BFI prices move closely together, the futures contract fails to track the fluctuations of the route price indices as closely.

Routes 1 and 1A are similar to each other as they are for Panamax based trans-Atlantic routes, but there are also some differences between them. Route 1 reflects cargo movements of Grain from US Gulf to a port in the Antwerp/Rotterdam/Amsterdam (ARA) area, and Route 1A is a time-charter route for a round-trip voyage from north-west Continent to US and back to north-west Continent. Therefore, route 1A consists of two legs: a ballast leg from Europe to US – as there are few dry bulk cargoes originating in Europe – and a laden leg from US to Europe. The cargoes transported in this leg are primarily Grain from US Gulf to ARA – like in route 1 – and to a lesser extent Coal and Iron Ore from the East Coast of USA. Therefore, there is a great degree of interdependence between these routes as charterers and/or shipowners may switch between the spot and time-charter route depending on the condition of the market. For instance, when freight rates are high, charterers prefer to time-charter their vessels fearing that freight rates will rise even further; this may be accentuated by the fact that there may be a relative shortage of tonnage in the US and a relative abundance of tonnage in Europe. Charterers will therefore choose to time-charter their vessels from Europe so as to secure the transportation of their commodities. The increased demand for time-charters in this case, relative to spot charters, will increase the level of time-charter rates.

6 The choice of a weekly hedging horizon is consistent with the empirical studies in other futures markets; see as well Kroner and Sultan (1993) and Gagnon and Lypny (1995, 1997).

7 When a holiday occurs on Wednesday, Tuesday’s observation is used in its place.
Fig. 1. Weekly Route 1, BFI and BIFFEX Prices.

Fig. 2. Weekly Route 1A, BFI and BIFFEX Prices.
The opposite takes place when freight rates are low. In this case, charterers prefer to secure the transportation of their commodities on a spot basis. This in turn, depresses time-charter rates and causes the level of spot rates to increase. This pattern is verified visually in Fig. 3, presenting the BFI against the Route 1A and Route 1 differential (i.e. Route 1A – Route 1). We can see that when freight rates are high, the time-charter Route 1A stands above Route 1. This difference was more prominent during the Spring of 1995, for instance, when BFI reached its highest level (2352 points on 1 May, 1995).  

Summary statistics of logarithmic spot and futures price differences are presented in Table 2. Based on the coefficients of excess kurtosis, spot and futures price series appear to be leptokurtic. Bera and Jarque (1980) tests indicate significant departures from normality; these departures seem to be more acute for the spot market data. The Ljung-Box Q statistic (Ljung and Box, 1978) on the first 24 lags of the sample autocorrelation function is significant for the spot price data indicating that serial correlation is present in the spot returns. Engle (1982) ARCH test and the $Q^2$ statistic, indicate the existence of heteroskedasticity in the spot price returns. Finally, Phillips–Perron tests (Phillips and Perron, 1988) on the levels and first differences indicate that the series are difference stationary.

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8 It should be stressed that there may be other factors, apart from the relative strength of the shipping markets, that may affect the relationship between routes 1 and 1A. For instance, regional imbalances in the availability of tonnage in different parts of the world, such as a shortage of tonnage in the US, may force charterers to time-charter their vessels from Europe. Another consideration may be voyage costs. In a time-charter, the charterer is responsible for the bunkering and other voyage costs. If charterers have access to low-cost bunkering then they may find it more cost efficient to charter their vessels on a time-charter basis.
5. Empirical results of VECM–GARCH-X models

Having identified that spot and futures prices are $I(1)$ variables, cointegration techniques are used next to examine the existence of a long-run relationship between these series. The lag length ($p$) in the VECM of Eq. (5), chosen on the basis of the SBIC (1978), is presented in Table 3. $^9$

Johansen (1991) LR test for the appropriateness of including an intercept term in the cointegrating vector indicate that restricting the intercept term to lie on the cointegrating vector is appropriate. The estimated $\lambda_{max}$ and $\lambda_{trace}$ statistics show that route 1 and route 1A freight rates stand in a long-run relationship with the futures price thus justifying the use of a VECM. The normalised coefficient estimates of the cointegrating vector, i.e. $\beta X_{t-1}$ in the same table, representing the long-run relationship between spot and futures prices, are used in the joint estimation of the conditional mean and the conditional variance. $^{10}$

<table>
<thead>
<tr>
<th>N $^a$</th>
<th>Skew $^b$</th>
<th>Kurt $^b$</th>
<th>J–B $^c$</th>
<th>$Q(24)^d$</th>
<th>$Q^2(24)^d$</th>
<th>ARCH$^e$</th>
<th>PP(4) in levels $^f$</th>
<th>PP(4) in first diffs $^f$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route 1</td>
<td>267</td>
<td>0.82 [0.00]</td>
<td>2.81 [0.00]</td>
<td>117.4</td>
<td>160.61</td>
<td>28.63</td>
<td>14.43</td>
<td>18.04</td>
</tr>
<tr>
<td>Route 1A</td>
<td>267</td>
<td>0.82 [0.00]</td>
<td>2.32 [0.00]</td>
<td>89.3</td>
<td>184.39</td>
<td>32.38</td>
<td>10.29</td>
<td>14.02</td>
</tr>
<tr>
<td>Futures</td>
<td>267</td>
<td>-0.34 [0.02]</td>
<td>0.90 [0.00]</td>
<td>14.2</td>
<td>36.67</td>
<td>14.11</td>
<td>0.01</td>
<td>3.89</td>
</tr>
<tr>
<td>1% c.v.</td>
<td>9.21</td>
<td>42.98</td>
<td>42.98</td>
<td>6.63</td>
<td>14.11</td>
<td>0.01</td>
<td>3.89</td>
<td>-3.46</td>
</tr>
<tr>
<td>5% c.v.</td>
<td>5.99</td>
<td>36.42</td>
<td>36.42</td>
<td>3.84</td>
<td>14.11</td>
<td>0.01</td>
<td>3.89</td>
<td>-2.88</td>
</tr>
</tbody>
</table>

$^a$ $N$ is the number of observations. The statistics are based on logarithmic differences.

$^b$ Skew and Kurt are the estimated centralised third and fourth moments of the data, denoted $\tilde{z}_3$ and $\tilde{z}_4 - 3$ respectively; their asymptotic distributions under the null are $\sqrt{T} \tilde{z}_3 \sim N(0, 6)$ and $\sqrt{T} (\tilde{z}_4 - 3) \sim N(0, 24)$.

$^c$ J–B is the Jarque–Bera (1980) test for normality; the statistic is $\chi^2$ distributed.

$^d$ $Q(24)$ and $Q^2(24)$ are the Ljung-Box (1978) $Q$ statistics on the first 24 lags of the sample autocorrelation function of the raw series and of the squared series; these tests are distributed as $\chi^2(24)$.

$^e$ ARCH(1) and (5) is the Engle (1982) test for ARCH effects; the statistic is $\chi^2$ distributed with 1 and 5 degrees of freedom respectively.

$^f$ PP is the Phillips and Perron (1988) unit root test; the truncation lag for the test is set to 4.

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$^9$ This refers to the lag length of an unrestricted VAR in levels as follows: $X_t = \sum_{i=1}^p A_i X_{t-i} + \epsilon_t$. A VAR with $p$ lags of the dependent variable can be reparameterised in a VECM with $p - 1$ lags of first differences of the dependent variable plus the levels terms.

$^{10}$ Notice that the estimates of the cointegrating vector are not restricted to be (1, 0, −1). This restriction would imply that the cointegrating vector reflects the lagged basis, i.e., the difference between spot (BFI) and futures (BIFFEX) prices and follows from the convergence of BFI and BIFFEX prices at the maturity day of the futures contract (see Fama and French, 1987). However, in this study, we consider the shipping routes which form part of the underlying asset (the BFI) and not the underlying asset itself. Although BIFFEX prices converge to the BFI at maturity, this does not necessarily imply that BIFFEX prices should also converge to the shipping routes which constitute the BFI. As additional supporting evidence that this restriction is not a valid hypothesis for our dataset, we perform tests on the cointegrating relationship using the Johansen (1988) and the Phillips and Hansen (1990) procedures. Using these methods, the hypothesis that the cointegrating vector is (1, 0, −1) is rejected at conventional levels of significance, for both routes. Finally, we also impose this restriction in the estimation of the GARCH models; LR tests, as well as the SBIC, indicate that the models with the unrestricted estimates of the cointegrating vector provide a better fit to our dataset. Results for all these tests are available from the authors on request.
The Berndt et al. (1974) algorithm is used to maximise the log-likelihood function. The most parsimonious GARCH and GARCH-X models, selected on the basis of LR tests, are presented in Table 4. Several observations merit attention. First, the speed of adjustment of spot and futures prices to their long-run relationship, measured by the \( a_s \) and \( a_f \) estimated coefficients respectively, are negative in the equation for the spot prices, while in the futures equation they are insignificant. This implies that in response to a positive deviation from their long-run relationship at period \( t-1 \), i.e. \( S_{t-1} > F_{t-1} \), the spot price in the next period will decrease in value while the futures price will remain unresponsive and suggests that for these routes, spot prices react more swiftly to return to their long-run relationship; this is consistent with the findings of Kavussanos 1996a,b in the examination of spot and forward freight rates.

Consider next the conditional variance part of the equations. LR statistics, testing the GARCH-X model against the simple GARCH model indicate that the former model is superior. The coefficients of the squared error correction term in the spot variance equations are significant, while the coefficients in the futures equation are insignificant. Short-run deviations from the long-run relationship between spot and futures prices affect primarily the volatility of spot price changes since, as the analysis of the ECT coefficients in the conditional mean equations suggests, spot prices are more responsive to deviations from the long-run relationship.

The term \( v \) is the estimate of the degrees of freedom of the conditional \( t \)-distribution. For large values of \( v \) (around 30), the \( t \)-distribution approaches the normal. The estimated value of \( v \) suggests that using the conditional normal distribution to describe the joint distribution of spot and futures returns would have been an incorrect assumption. To demonstrate that this model adequately captures the leptokurtosis present in our data, the theoretical kurtosis implied by a \( t \)
Table 4

Maximum likelihood estimates of the ECM–GARCH models

\[ \Delta S_t = \sum_{i=1}^{p-1} a_{S,t} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{S,t} \Delta F_{t-i} + \varepsilon_{S,t} \]

\[ \Delta F_t = \sum_{i=1}^{p-1} a_{F,t} \Delta S_{t-i} + \sum_{i=1}^{p-1} b_{F,t} \Delta F_{t-i} + \varepsilon_{F,t} \]

\[ \varepsilon_t = \left( \begin{array}{c} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{array} \right) | \Omega_{t-1} \sim \text{Student-}t(0, H_t, \nu) \]

\[ H_t = \begin{pmatrix} h_{SS,t} & h_{SF,t} \\ h_{FS,t} & h_{FF,t} \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix} \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix} + \begin{pmatrix} \varpi_{11} & 0 \\ 0 & \varpi_{22} \end{pmatrix} \tilde{a}_{t-1} \tilde{\varepsilon}_{t-1} \begin{pmatrix} \varpi_{11} & 0 \\ 0 & \varpi_{22} \end{pmatrix} + \begin{pmatrix} d_{11} \\ d_{12} \end{pmatrix} \tilde{e}_{t-1} \begin{pmatrix} d_{11} \\ d_{12} \end{pmatrix} \]

<table>
<thead>
<tr>
<th>Route 1</th>
<th>Route 1A</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM-GARCH</td>
<td>ECM-GARCH-X</td>
</tr>
<tr>
<td>Mean equation</td>
<td></td>
</tr>
<tr>
<td>( \varpi_S )</td>
<td>(-0.091 (0.019)^a )</td>
</tr>
<tr>
<td>( \varpi_{S,1} )</td>
<td>(0.469 (0.049)^a)</td>
</tr>
<tr>
<td>( \varpi_{S,2} )</td>
<td>(0.207 (0.041)^a)</td>
</tr>
<tr>
<td>( \varpi_F )</td>
<td>(-)</td>
</tr>
<tr>
<td>( \varpi_{F,1} )</td>
<td>(0.181 (0.072)^a)</td>
</tr>
<tr>
<td>( \varpi_{F,2} )</td>
<td>(-)</td>
</tr>
<tr>
<td>( \varpi_{F,2} )</td>
<td>(-0.156 (0.061)^a)</td>
</tr>
<tr>
<td>Variance</td>
<td></td>
</tr>
<tr>
<td>( c_{11} )</td>
<td>(0.012 (0.003)^a)</td>
</tr>
<tr>
<td>( c_{12} )</td>
<td>(0.039 (0.147))</td>
</tr>
<tr>
<td>( c_{22} )</td>
<td>(7 \times 10^{-4} (6.058))</td>
</tr>
<tr>
<td>( \varpi_{11} )</td>
<td>(0.349 (0.085)^a)</td>
</tr>
<tr>
<td>( \varpi_{22} )</td>
<td>(0.056 (0.235))</td>
</tr>
<tr>
<td>( \beta_{11} )</td>
<td>(0.847 (0.076)^a)</td>
</tr>
<tr>
<td>( \beta_{12} )</td>
<td>(0.162 (3.713))</td>
</tr>
<tr>
<td>( d_{11} )</td>
<td>(-)</td>
</tr>
<tr>
<td>( d_{22} )</td>
<td>(-)</td>
</tr>
<tr>
<td>( \nu )</td>
<td>(6.475 (2.356)^a)</td>
</tr>
<tr>
<td>LL</td>
<td>(1103.88)</td>
</tr>
<tr>
<td>LR</td>
<td>(5.14 \sim \chi^2(2))</td>
</tr>
<tr>
<td>AIC</td>
<td>(-2181.77)</td>
</tr>
<tr>
<td>SBIC</td>
<td>(-2135.14)</td>
</tr>
</tbody>
</table>

\(^a\) Significance at the 1% level. Numbers in parentheses are asymptotic standard errors. The coefficients which are restricted to be zero are denoted by a dash (–).

\(^b\) Significance at the 5% level. Numbers in parentheses are asymptotic standard errors. The coefficients which are restricted to be zero are denoted by a dash (–).

\(^c\) \( \nu \) is the estimate of degrees of freedom from the \( t \)-distribution.

\(^d\) LL is the maximum value of the log-likelihood function.

\(^e\) LR is the likelihood ratio statistic for the restriction \( d_{11} = d_{12} = 0 \). It is \( \chi^2(2) \) distributed with 5% critical value of 5.99.
distribution is presented in Table 5. ¹¹ Consider for instance route 1A: the actual kurtoses of the standardised residuals, are 5.77 and 3.84 for the spot and futures equations, respectively. After the inclusion of the ECT in the conditional variance equation, the theoretical kurtosis implied by the estimated degrees of freedom is 7.63, which is closer to the observed kurtoses of 5.06 and 3.84 of the spot and futures returns. Therefore, the GARCH-X model captures the leptokurtosis of spot and futures returns more closely than the simple GARCH model. This is consistent with the results of Hogan et al. (1997) who find that the theoretical kurtosis of a t-distribution gets closer to the observed kurtosis of the S&P 500 spot and futures returns after the inclusion of additional explanatory variables in the equation of conditional variance.

¹¹ The theoretical kurtosis is computed as $3(v-2)(v-4)^{-1}$; $v > 4$; see Bollerslev (1987). For instance if $v = 4.77$ the theoretical kurtosis is 10.725.
The degree of persistence in variance for each route is measured by the sum of $\alpha_{i1}^2 + \beta_{i1}^2$ coefficients. These measures, also presented in Table 5, indicate a varying degree of persistence across the different routes, although in all cases the sum is less than unity implying that the GARCH system is covariance stationary. Similar conclusions emerge when we consider the half-life of shocks to volatility. Finally, diagnostic tests on the standardised ARCH residuals, $\epsilon_t / \sqrt{h_t}$, and standardised squared ARCH residual, $\epsilon_t^2 / h_t$, indicate that the selected models are well specified. In addition, sign and size bias tests (see Engle and Ng, 1993) indicate that the response of volatility to shocks (news) is “symmetric” and is not affected by the magnitude of the shock, providing further evidence that the GARCH specification is appropriate. \(^{12}\)

6. Optimal models for hedge ratio estimation and forecasting

Following estimation of the GARCH models, measures of the time-varying variances and covariances are extracted and used to compute the time-varying hedge ratios of Eq. (4). Hedge ratios from the GARCH-X models for routes 1 and 1A are presented in Fig. 4 and Fig. 5 together with the conventional hedge ratios, obtained from the OLS model of Eq. (1). It can be seen that the conditional hedge ratios are clearly changing as new information arrives in the market.

To formally compare the performance of each type of hedge, we construct portfolios implied by the computed hedge ratios each week and calculate the variance of the returns to these portfolios over the sample, i.e., we evaluate

$$\text{Var}(\Delta S_t - \gamma_t^* \Delta F_t),$$

(8)

where $\gamma_t^*$ are the computed hedge ratios. We consider the hedge ratios from the two GARCH specifications, the OLS hedge of Eq. (1) and a naive hedge by taking a futures position which exactly offsets the spot position (i.e., setting $\gamma_t^* = 1$). The variance of the hedged portfolios is compared to the variance of the unhedged position, i.e., $\text{Var}(\Delta S_t)$. The larger the reduction in the unhedged variance, the higher the degree of hedging effectiveness. Our results are presented in Table 6. The GARCH-X model outperforms all the other hedges considered as is expected by the model’s superior statistical properties in explaining the dynamics of spot and futures returns. On the other hand, the constant hedge ratio provides greater variance reduction than the simple GARCH model. Finally, the naive hedge is the worst hedging strategy since, using a hedge ratio of 1, increases the portfolio variance from the unhedged position. \(^{13}\)

The in-sample performance of the alternative hedging strategies gives an indication of their historical performance. However, investors are more concerned with how well they can do in the future using alternative hedging strategies. So, out-of-sample performance is a more realistic way to evaluate the effectiveness of the conditional hedge ratios. For that, we withhold 80 observations of the sample (that is after 17 April, 1996, representing a period of one and a half years) and

\(^{12}\) See the note in Table 5 for the description of these tests.

\(^{13}\) As pointed out by an anonymous referee, the models for routes 1 and 1A may be estimated jointly. We investigated this possibility; however, the resulting models generate hedge ratios whose hedging performance is worse than that achieved by the individual GARCH-X models. Since the objective of this paper is to estimate the time-varying hedge ratios that provide the largest variance reduction in the BFI routes, results from these models are not presented here.
Fig. 4. Route 1 Time-Varying and Conventional Hedge Ratios.

Fig. 5. Route 1A Time-Varying and Conventional Hedge Ratios.
estimate the two conditional models using only the data up to this date. Then, we perform one-step ahead forecasts of the covariance and the variance as follows:

\[
E(h_{SF,t+1}|\Omega_t) = c_{11}c_{12} + \alpha_{11}\alpha_{22}c_{SF,t}c_{F,t} + \beta_{11}\beta_{22}h_{SF,t} + d_{11}d_{22}z^2_t,
\]

\[
E(h_{FF,t+1}|\Omega_t) = c_{12}^2 + c_{22}^2 + \alpha_{22}^2c_{F,t}^2 + \beta_{22}^2h_{FF,t} + d_{22}^2z^2_t.
\]

The one step ahead forecast of the hedge ratio is computed as

\[
E(\gamma_{t+1}|\Omega_t) = E(h_{SF,t+1}|\Omega_t)/E(h_{FF,t+1}|\Omega_t).
\]

The following week (24 April, 1996), this exercise is repeated, with the new observation included in the data set. We continue updating the models and forecasting the hedge ratios until the end of our data set.\(^{14}\)

\(^{14}\) In practice, an actual hedger will perform the modelling procedure described in Section 4 for each new observation in the out-of-sample tests, i.e., he will model the conditional mean of the series so as to obtain the estimates of the cointegrating vector and then he will estimate jointly the conditional mean and the conditional variance given these estimates of the cointegrating relationship. However, use of this procedure in our case would make the estimation of the out-of-sample tests computationally cumbersome. In order to overcome this problem, we update the estimates of the cointegrating vector every twenty observations. Hence, for the first out-of-sample tests, we estimate the coefficients of the cointegrating vector using the data up to 17 April 1996. Then, for the next 20 observations the ECM-GARCH system is re-estimated using these estimates of the cointegrating vector, and so on.
hedge ratios and thus for the issue of hedging effectiveness. The short run error from the cointegrating relationship is therefore a useful variable in modelling the conditional variance as well as the conditional mean of the series.

The reduction in the out-of-sample portfolio variances relative to the OLS hedge achieved by the GARCH-X model (0.43% for route 1 and 5.07% for route 1A) compares favourably with the findings in other futures markets. Kroner and Sultan (1993) report percentage variance improvements of the GARCH hedge relative to the OLS hedge ranging between 4.64% and 0.96% for 5 currencies; Gagnon and Lypny (1995, 1997) find 1.87% variance reduction for the Canadian interest rate futures and 0.70% variance reduction for the Canadian stock index futures; Bera et al. (1997) estimate 2.74% and 5.70% variance reductions for the corn and soybean futures. However, none of these studies considers the GARCH-X model that we propose above.

Despite the superior performance of the GARCH-X model compared to the GARCH and the OLS hedges, the proposed hedging strategy fails to eliminate a large proportion of the variability of the unhedged portfolio; the greatest variance reduction is 23.25% in route 1A (17.04% in route 1). This is well below the variance reduction over the unhedged position evidenced in other studies: 57.06% for the Canadian interest rate futures (Gagnon and Lypny, 1995); 69.61% and 85.69% for the corn and soybean futures (Bera et al., 1997); and 97.91% and 77.47% for the SP500 and the Canadian Stock Index futures contract (Park and Switzer, 1995), and reflects the fact that futures prices do not capture accurately the fluctuations on the individual routes that constitute the BFI, but rather follow the movements of the BFI itself.

The above evidence suggests that the hedging effectiveness of the futures contract may be improved by restructuring the composition of the BFI so as to reflect trade flows which are homogeneous in terms of commodities and cargo sizes. Hence, the forthcoming exclusion of the capsize routes from the BFI and the introduction of the Baltic Panamax Index (BPI) as the new underlying asset of the BIFFEX contract, from November 1999, is likely to have a beneficial impact on the hedging performance of the market. As a result, futures contracts may manage to eliminate a larger proportion of the variance of the unhedged portfolio and their effectiveness may compare favourably with the results in other markets. Whether this imminent revision of the index will have a beneficial impact on the market is an issue that remains to be seen by the reaction of the agents in the market.

7. Conclusions

This paper has examined the hedging effectiveness of the freight futures contract and investigated alternative methods for computing more efficient hedge ratios. In- and out-of-sample tests indicate that time-varying hedge ratios estimated from VECM-GARCH-X models outperform alternative specifications in reducing market risk. Market agents can benefit from this framework by computing superior hedge ratios and thus controlling more efficiently their freight rate risk. This risk reduction, however, is lower than that evidenced in other commodity and financial futures markets in the literature. This is thought to be the result of the heterogeneous composition of the BFI in terms of vessel sizes and cargo routes. Further research will examine the effectiveness of the BIFFEX contract across the other shipping routes which constitute the BFI. It is suspected that the results are similar. Enhanced homogeneity of the BFI may increase its hedging
effectiveness and possibly its use for hedging purposes. This by itself indicates that the imminent introduction of the BPI as the underlying asset of the BIFFEX contract is likely to have a beneficial impact on the market.

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