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Optimal hedging efficiency in global freight markets: Comparing FFAs and time charter strategies

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Abstract

The paper aims to mitigate financial risk in highly volatile shipping freight markets by employing a dynamic hedging model. The primary criterion for evaluating the effectiveness of various methods for estimating optimal hedge ratios through Forward Freight Agreements (FFAs) is the minimum variance hedging rule. Four different methods are utilized to estimate two types of hedge ratios. The first type, a static hedge ratio, is calculated using the OLS and ECM methods. The second type, a time-varying hedge ratio, is determined through a bivariate GARCH model and a Rolling Window OLS method. Additionally, the hedging effectiveness of the traditional method of hedging, time chartering, is compared to the more modern and sophisticated shipping derivatives methods using the coefficient of variation.

1. Introduction

In recent years, globalization has become a common reality and, as a result, the transportation of commodities from one continent to another has become a crucial factor in global economic growth. A significant portion (80 %) of world trade is conducted by ships. This is evident in the substantial increase in transport volume, rising from 2.8 billion tons in 1986 to over 9 billion tons in 2022.

The freight market is marked by considerable complexity, posing challenges for shipowners, charterers, and operators who face significant financial risks due to the extreme volatility in freight prices. This volatility can be attributed to various factors, including vessel supply, demand and supply for commodities, shipyard availability, scrapping, and more. Additionally, industrial growth has not only altered shipping routes over the years, but has also influenced the quantities of delivery services. Consequently, the level of freight rates is responsive to changes in overall economic growth, making the freight market a prominent topic in financial literature.

From a financial standpoint, freight rates are integral to the commodities market. However, they possess unique characteristics distinct from other markets. Primarily, freight rates can be viewed as the cost of services, rather than the cost of products, rendering them non-storable. Moreover, the

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spot market for freight rates displays notable volatility, introducing significant risks for all market participants. This volatility underscores the necessity for financial hedging tools, supplementing the traditional time charter arrangements.

Derivatives in freight markets have a history dating back to the late 1980s, when a freight future contract based on the dry bulk freight index was introduced. These contracts were known as Baltic International Freight Futures Exchange Contracts (BIFFEX). Launched on May 1, 1985, BIFFEX contracts were linked to the BFI index. However, due to unsatisfactory hedging performance, they were eventually delisted in April 2002.

Following those initial contracts, several diverse freight derivatives have been introduced, with tailor-made contracts like Forwards or Futures becoming prevalent. One of the most noteworthy types among these contracts are the Forward Freight Agreements (FFA). FFAs are negotiated over the counter, and their underlying assets are either a specific shipping route or a combination of routes (Alizadeh & Nomikos, 2009). In recent years, new derivative products, such as options in freight rates, have also been introduced.

This research has several motivations. Firstly, it is an aim to examine hedging performance using various estimation methods in freight markets, utilizing updated Forward Freight Agreement data. Additionally, assessing Hedge Ratios in the freight markets is focused on, employing a set of recent methods not previously applied in this context. A comparison and contrast of the empirical findings with similar studies conducted in the past is also conducted.

Moreover, given how some studies suggest that complex econometric models may not outperform standard Ordinary Least Squares (OLS) regression models in estimating optimal Hedge Ratios in commodity markets, this study aims to investigate this assertion. In the final part of this research, the hedging effectiveness of freight derivatives with the most common method of hedging, Time-Charter (T/C) contracts, is compared.

The objectives of the study are threefold. Firstly, to evaluate and manage financial risks arising from the volatility of freight rates. Secondly, to articulate and estimate a dynamic hedging model tailored to shipping freight markets. Finally, to test and compare various methods for effective hedging of freight rates.

The study is structured as follows: In Section 2, a literature review and discussion of the outcomes of comparable studies in other derivative markets are conducted. Section 3 furnishes details about the dataset utilized in the current study. In Section 4, the methodology for estimating hedge ratios and evaluating the effectiveness of each estimated hedge ratio and time chartering are delved into. Section 5 is dedicated to presenting and discussing the results and, finally, Section 6 provides a summary of the study. Additionally, there is an appendix containing correlogram graphs.

2. Literature review

A considerable number of research studies and papers have aimed to find the most appropriate method to estimate the hedge ratio. Two different approaches are employed to determine this: The first approach involves maximizing utility (Cotter & Hanly, 2012), while the second one focuses on minimizing volatility, or in other words, minimizing risk (Ripple & Moosa, 2007). Earlier studies (Ederington, 1979; Johnson, 1960; Stein, 1961) utilize portfolio theory to estimate a hedge ratio that minimizes variance between spot and futures price changes. From a more theoretical perspective, an optimal minimum-variance hedge ratio of a hedged portfolio is a type of utility maximization approach (Ederington, 1979; Johnson, 1960; Lien & Tse, 2002; Myers & Thompson, 1989). This minimum-variance framework is widely used because it is simple to compute and easy to understand (Chen et al., 2003).

In their work, Adland and Jia (2017) delve into the various origins of physical basis risks within the freight markets, emphasizing distinctions in timing and vessel specifications. Building on this, Adland and Alizadeh (2018) demonstrate that there exists co-integration between physical timecharter rates and the prices of a collection of FFA contracts with equivalent durations in the dry bulk market. They interpret the mean-reverting differential as a representation of disparate credit risk and a convenience yield associated with gaining access to physical transportation.

From the existing literature, two pivotal questions arise. The first concerns model specification. Ghosh (1993) asserts that the determination of a minimum-variance hedge ratio hinges on the chosen econometric model. Wang et al. (2015) support this notion, suggesting that, despite the application of numerous advanced estimation methods beyond OLS for hedge ratio estimation, the optimal approach remains uncertain. Conversely, several studies suggest that using a straightforward econometric model for hedge ratio estimation can yield comparable results to those obtained with more intricate methodologies (Lence, 1995; Lien et al., 2016; Moosa, 2011).

According to Alexander and Barbosa (2007), neither a complex model, such as time-varying conditional covariance, nor an Error Correction model (ECM) surpasses the effectiveness of the OLS model. Moreover, findings from Copeland and Zhu (2006) argue that employing a sophisticated model for hedge ratio estimation does not add significant value, compared to the simplicity of the OLS approach.

According to Moosa (2003), the measure of success or failure in estimating hedging effectiveness relies on the correlation between the price of the unhedged position and the price of the hedged instrument, rather than on model specifications.

The minimum variance hedge ratio is determined by the ratio of the unconditional covariance between spot and future price changes, ΔS_t and ΔF_t, respectively, to the variance of future price changes ΔF_t,

$$h = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)}.$$

In a linear equation representing the relationship between the price changes of the spot and future market, the hedge ratio is equivalent to the slope (b) in the regression equation $\Delta S_t = a + b\Delta F_t + u_t$, where S_t are the spot prices, F_t the future prices, and u_t an error term (Ederington, 1979). The efficacy of this hedge ratio is assessed by the value of R^2. A higher R^2 indicates greater effectiveness of the hedge ratio.

The most common method of estimating hedge ratios, in theory and in practice, is the classic OLS model, which uses the spot freight price as the dependent variable, and the forward or future price of the hedged asset as the independent variable (Benet, 1992; Ederington, 1979; Junkus & Lee, 1985; Malliaris & Urrutia, 1991).

The prevalent OLS model, employing variables such as level prices or changes in exchange rates, features the spot price level or change as the dependent variable and the hedged asset, like a forward or future price level or change as the independent variable. This method, widely used for hedge ratio estimation, is supported both in theory and in practical applications (Benet, 1992; Ederington, 1979; Junkus & Lee, 1985; Malliaris & Urrutia, 1991).

However, a crucial aspect in determining the model lies in the choice of the variable type, whether it should be the price level or the price change. Witt et al. (1987) argue in favor of the price level model, while Hill and Schneeweis (1981) and Wilson (1983) advocate for the price change or return model. Each approach has its own advantages and drawbacks.

Several studies by Ghosh (1993, 1995, 1996) highlight that using a price level hedge ratio neglects short-term dynamics, whereas employing a price change hedge ratio overlooks long-term dynamics. To enhance the model, Ghosh (1995) introduced an error correction term in the first-difference model to account for the implied long-term relationship. This study posits that omitting a cointegration relationship between variables (spot and forward rates), represented by the error correction term, results in a smaller hedge ratio compared to the optimal ratio. Lien and Tse (2002) provide the first mathematical proof of this outcome, demonstrating that estimating the hedge ratio using a first-difference model leads to underhedging by agents.

Various studies apply the OLS methodology across different markets. Specifically, in freight futures markets, Thuong and Visscher (1990) utilize this method to estimate the minimum variance hedge ratio. The consistent findings across these studies indicate that both commodity and financial futures demonstrate strong hedging performance, with R^2 values ranging between 0.80 and 0.95.

Contrastingly, the hedging performance in the freight market is notably subpar. This outcome is attributed to the composition of BIFFEX contracts. Notably, more promising results emerge when FFAs are employed, as demonstrated in the empirical studies conducted by Kavussanos and Nomikos (2000).

Estimating the hedge ratio using the OLS method results in a static measure. Beyond OLS, econometric approaches like ECMs can be employed to introduce long-term dynamics, as previously discussed. Engle and Granger (1987) propose that, when time series are cointegrated, an error correction representation of the data is present. Kenourgios, Samitas, and Drosos (2008) have conducted a comparative analysis of various methods for estimating hedge ratios in S&P 500 stock index futures contracts to assess their respective hedging effectiveness.

The utilization of the ECM introduced by Engle and Granger (1987) to estimate the optimal minimum variance hedge ratio for corn, soybeans, and wheat is documented in Myers and Thompson (1989). Additionally, Chou et al. (1996) have discovered that hedging under the ECM model outperforms the traditional OLS model when applied to Nikkei spot and futures indices.

Furthermore, the conventional OLS method for estimating the optimal hedge ratio has faced criticism. This skepticism is rooted in concerns about serial correlation and heteroskedasticity in the error term, arising from the relationship between spot and forward rates (Herbst et al., 1993; Hill & Schneeweis, 1981).

The primary drawback of the static hedge ratio lies in its constancy, which contrasts with the time-varying nature of asset prices, all of which exhibit evolving distributions over time. This fundamental mismatch underscores the crucial argument that the hedge ratio should be dynamic and responsive to changes over time.

The second challenge within the literature revolves around the dynamics of the hedge ratio, addressing whether it remains constant or undergoes changes over time (time-varying). Additionally, there is a debate over whether to employ a conditional or unconditional probability distribution for its estimation. An alternative approach involves utilizing a dynamic time-varying hedge ratio based on unconditional moments, such as the ARCH and GARCH family of models. In GARCH family models, it is assumed that the covariance and variance of returns are time-varying.

Research on time-varying hedge ratios has been conducted by Cecchetti et al. (1988), Kroner and Sultan (1993), Sephton (1993), Brooks and Chong (2001), Park and Jei (2010), and Hatemi-J and El-Khatib (2012). Cecchetti et al. (1988) utilize a bivariate GARCH model to estimate the optimal hedge for commodities futures, comparing the variance reduction between a constant and time-varying hedge ratio.

To calculate a time-varying hedge ratio, the family of ARCH models, introduced by Engle (1982), is employed to measure the unconditional covariance between spot and future price changes. The importance of cointegration between spot and future prices is underscored by Kroner and Sultan (1993), Chou et al. (1993), and Lien and Tse (1999). Choudhry (1997) utilizes a GARCH (1,1) model with a BEKK formation to examine spot and futures stock indices.

Kavussanos and Visvikis (2006) have pioneered empirical work on FFAs, as most studies focus on the delisted BIFFEX futures contract due to data availability issues with FFAs. In a study spanning 2004 to 2008, Kavussanos and Visvikis (2010) investigated in- and out-of-sample variance reduction using weekly data on route C4[†] and a basket of time-charter routes. Hedge ratios were calculated using the conventional OLS method, VECM, and VECM-GARCH-X. Depending on the model, in-sample results demonstrated a variance reduction ranging from 56 to 60 % on the C4 route

[†] Route C4: Richards Bay to Rotterdam.

and 55 % to 64 % on the basket of time-charter routes. Out-of-sample variance reduction varied from 79 % to 86 % for the C4 route and 63 to 66 % for the basket of time charters. Notably, the VECM-GARCH method emerged as the optimal choice for estimating the hedge ratio (Kavussanos & Visvikis, 2010).

In their study, Kou and Luo (2015) explore the connection between ship prices and freight rates, considering structural changes and assuming that the freight rate adheres to an extended mean-reverting process. Their findings reveal that the impact of changes in freight rates on ship prices remains constant, despite structural shifts. Meanwhile, Alizadeh et al. (2017) incorporate investor behavior and diversity among ship investors in their research. They observe that momentum-driven investment tends to elevate volatility, whereas investment demand rooted in fundamentals serves to diminish ship price volatility.

In their study, Alexandridis et al. (2017) examine the lead-lag dynamics among FFAs (Forward Freight Agreements), freight options, and the physical market. They discover that informational leadership lies with the freight futures market, as it precedes movements in physical spot rates. Meanwhile, Yin et al. (2017) employ a VAR (Vector Autoregression) and VECM (Vector Error Correction Model) framework to uncover the long-term and mutually causal relationship between spot and FFA prices. Their findings indicate that cointegration, along with exogenous factors such as market demand and supply, plays a dominant role in shaping the long-term dynamics of these markets.

The Rolling Window OLS (RW-OLS) method, slated for use in hedge ratio estimation, finds applications in various financial markets. Byström (2003) highlights its relevance in the electricity market, while Moon et al. (2009) and Bhattacharya et al. (2011) showcase its utility in securities and stock markets, respectively. Numerous studies in these domains demonstrate the superior hedging effectiveness achieved by a hedge ratio estimated with RW-OLS, compared to more complex GARCH models.

Contrary to the belief that complex econometric models might enhance estimation, Alexander and Barbosa (2007) have discovered no evidence supporting the notion that these models outperform a simple OLS regression for estimating the optimal hedge ratio. Additionally, time-varying models face criticism for introducing excessive noise that can negatively impact the cost-effectiveness of hedges (Copeland & Zhu, 2006).

In this study, two key questions prevalent in the literature are addressed. The first pertains to model specification, while the second revolves around the dynamics of the hedge ratio, specifically, whether an investor should opt for a static or a time-varying hedge ratio. To investigate these issues, the hedging effectiveness of freight futures is assessed using data provided by Clarkson's Ltd. Four different methods to estimate hedge ratios are employed.

The static hedge ratio is computed through ordinary least squares (OLS) and an error correction model (ECM). Additionally, time-varying hedge ratios are estimated using the VECH-GARCH model and Rolling Window OLS (RW-OLS), marking the first instance of employing the latter method in the freight derivatives market, to the best of the author's knowledge. Subsequently, a comparative analysis of the hedging effectiveness of each estimated hedge ratio is conducted, including the traditional Time Charter (T/C) contracts.

3. Data and methodology

For this research, weekly data comprising spot, time charter, and FFA prices, sourced from Clarkson's Ltd, are utilized. The data spans from 2008 to 2017, encompassing approximately 468 prices for each time series. To minimize basis risk, the one-month contract for FFAs are specifically focused on. Additionally, this research centers around the BCI 7 route for spot, time charter, and FFA prices.

There are several reasons for this preference for weekly data. Firstly, a week provides a reasonable timeframe for rebalancing the hedging position. Secondly, weekly prices offer a robust and substantial sample of observations for further research within this timeframe. Lastly, the choice of weekly observations aligns this study with other research in freight markets, such as the work conducted by Kavussanos and Visvikis (2006).

In a broader context, the aim of this research is to address a specific question through the application of scientific procedures, as outlined by Kothari in 2008. More specifically, the primary objective of this study is to identify the most appropriate method for estimating the hedge ratio. This pursuit is driven by the overarching goal of minimizing basis risk and safeguarding market participants from the impacts of price volatility.

One crucial aspect involves conducting tests on the time series to assess stationarity and explore potential long-run relationships through cointegration. To accomplish this, a comprehensive set of appropriate unit root tests has been employed.

According to Hull (2012), the determination of the optimal hedge ratio involves an initial definition of ΔS_t as the first differences in spot prices, and ΔF_t as the first differences in future prices. In this context, σ_s denotes the standard deviation of S_t, σ_F represents the standard deviation of ΔF_t, p signifies the correlation coefficient between ΔS_t, and ΔF_t, and h denotes the hedge ratio.

In the scenario of a short hedge, characterized by being long in the asset and short in the futures contract, the variation in the value of the hedger's position throughout the hedge's duration is expressed by $(\Delta S_t - h \cdot \Delta F_t)$. Conversely, for a long hedge, the pertinent equation is articulated as $(h \cdot \Delta F_t - \Delta S_t)$. This implies that a negative value in the optimal hedge ratio conveys a preference for a long hedge.

The variances of the two hedged portfolios (long spot and short futures, or long futures and short spot) will be equivalent. These can be estimated by:

$$var(\Delta S_t - h\Delta F_t) = var(\Delta S_t) + var(h\Delta F_t) - 2cov(\Delta S_t, h\Delta F_t) \Rightarrow$$
$$var(\Delta S_t - h\Delta F_t) = var(\Delta S_t) + h^2 var(\Delta F_t) - 2h \cdot p \cdot var(\Delta S_t) \cdot var(\Delta F_t)$$

Therefore, the variance of the change in the value of the hedged position is expressed as:

$$\sigma^2_{portfolio} = \sigma_s^2 + h^2 \cdot \sigma_F^2 - 2hp\sigma_s\sigma_F$$

Minimizing the aforementioned expression and solving the equation for h,:

$$h = p\frac{\sigma_s}{\sigma_F} = \frac{\sigma_{SF}}{\sigma_F^2},$$

is obtained, where $p = {}^{\sigma_{SF}}/_{\sigma_S \cdot \sigma_F}$ the correlation coefficient, and σ_{SF} = the covariance between ΔS and ΔF.

The earlier formula provides a static hedge ratio and is estimable through historical data. Conversely, if there is a necessity to calculate a time-varying hedge ratio using the same minimization approach and employing a multivariate GARCH model, the previously mentioned expression is substituted by:

$$h_t = p_t \frac{\sigma_{S,t}}{\sigma_{F,t}} = \frac{\sigma_{SF,t}}{\sigma_{F,t}^2}$$

In this research, four different methods are employed to estimate two distinct types of hedge ratios. The first type is the Static Hedge Ratio, and according to the existing literature, two widely utilized approaches involve estimating an OLS model and, alternatively, estimating an ECM.

The initial econometric method involves a straightforward linear regression model utilizing the Ordinary Least Squares (OLS) method to estimate the coefficient 'b,' representing the hedge ratio. Numerous academic studies operate under the assumption that the primary goal of hedging is to minimize the variance of returns in the hedged portfolio. In such instances, the suitable hedge ratio, indicating the number of units of the futures asset to sell per unit of the spot asset held, is determined by the estimated slope 'b' in a regression. Here, the dependent variable comprises a time series of spot returns, while the independent variable comprises a time series of future returns (Brooks, 2008).

The equation used for estimation is:

$$\Delta S_t = a + b\Delta F_t + u_t,$$

where ΔS_t are the first differences in spot prices, and ΔF_t are the first differences in future prices. The slope b of this linear equation is $b = \frac{\sigma_{fs}}{\sigma_f^2}$, and represents the hedge ratio. This model must satisfy specific assumptions to yield reliable results. Firstly, the variance of the error term should be constant and finite, and the errors should be linearly independent of each other. In other words, the errors should exhibit homoscedasticity and lack serial autocorrelation.

The second econometric model employed for estimating the static hedge ratio is the Error Correction Model (ECM). The ECM serves as a dynamic model for the correlation in returns, and the t-statistics associated with its estimated coefficients offer valuable insights into the lead-lag behavior between returns (Alexander, 2001). The nomenclature 'error correction' is aptly chosen because the model is designed to correct short-run deviations from equilibrium. Consequently, the ECM is structured as follows:

$$\Delta S_t = a_1 + \sum_{i=1}^{m_1} \beta_{1i}\Delta S_{t-1} + \sum_{i=1}^{m_2} \beta_{2i}\Delta F_{t-1} + \gamma_1 z_{t-1} + \varepsilon_{1t}$$

$$\Delta F_t = a_2 + \sum_{i=1}^{m_3} \beta_{3i}\Delta F_{t-1} + \sum_{i=1}^{m_4} \beta_{4i}\Delta S_{t-1} + \gamma_2 z_{t-1} + \varepsilon_{2t},$$

where Δ is the first differences, and $z = x - ay$ is the disequilibrium term. The lag lengths and coefficients are determined through the estimation of OLS regression. The ECM yields the covariance between ΔS_t and ΔF_t, along with the variance of ΔF_t. This allows us to estimate the hedge ratio using the ECM model by the following formula:

$$h = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)}$$

The second type of hedge ratio, known as the Time-Varying Hedge Ratio, is estimated using two distinct methods. The initial approach involves estimating variances and covariances through a Vector Autoregressive Conditional Heteroskedasticity (VECH) Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The second method employs a Rolling Window OLS model (RW-OLS) for estimation.

Multivariate GARCH models share a similar essence with their univariate counterparts, but with the added advantage that they specify expressions for how variances and covariances evolve over time. Prominent GARCH models, such as the VECH and BEKK models, have been extensively proposed in the literature.

In the context of estimating a time-varying hedge ratio, a bivariate GARCH model is employed to estimate a time-varying covariance matrix. In this research, a diagonal VECH GARCH is used. The hedge ratio is estimated by $h_t = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)}$. The VECH model requires the estimation of 21 parameters, which are given by the equations:

$$h_{11t} = c_{11} + a_{11}u_{1t-1}^2 + a_{12}u_{2t-1}^2 + a_{13}u_{1t-1}u_{2t-1} + b_{11}h_{11t-1} + b_{12}h_{22t-1} + b_{13}h_{12t-1}$$
$$h_{22t} = c_{21} + a_{21}u_{1t-1}^2 + a_{22}u_{2t-1}^2 + a_{23}u_{1t-1}u_{2t-1} + b_{21}h_{11t-1} + b_{22}h_{22t-1} + b_{23}h_{12t-1}$$
$$h_{12t} = c_{31} + a_{31}u_{1t-1}^2 + a_{32}u_{2t-1}^2 + a_{33}u_{1t-1}u_{2t-1} + b_{31}h_{11t-1} + b_{32}h_{22t-1} + b_{33}h_{12t-1},$$

h_{iit} represents the conditional variance at time t of the returns of spot and future prices, and the last equation represents the conditional covariance between the returns of spot and futures prices. The above equations in matrices expression is given by:

$$VECH(H_t) = C + A \cdot VECH(\Xi_{t-1}\Xi'_{t-1}) + B \cdot VECH(H_{t-1}), \Xi_t|\psi_{t-1} \sim N(0, H_t)$$
$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix}, \Xi_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}, C = \begin{bmatrix} c_{11} \\ c_{21} \\ c_{31} \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$
$$B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}, VECH(H_t) = \begin{bmatrix} h_{11t} \\ h_{22t} \\ h_{12t} \end{bmatrix},$$

where H_t is a 2×2 conditional variance-covariance matrix, Ξ_t is a 2×1 innovation (disturbance) vector, ψ_{t-1} are the information set at time t-1, C is a vector of constant parameters, A, B 3×3 matrices are parameters, and VECH(.) denotes the column-stacking operator applied to the upper portion of the symmetric matrix. The estimation of the above model requires the estimation of 21 parameters, 3 parameters of C matrix, and 9 parameters of each one of A and B matrices. The dependence of conditional variances and covariances is evident in their reliance on the lagged values of all conditional variances and covariances between spot returns and future returns.

The estimation of such models is time-consuming, even in the case of just two assets. As previously noted, the model requires the estimation of 21 parameters. Consequently, to streamline the estimation process, a constrained version, known as the diagonal VECH GARCH model, is employed. This model, developed by Bollerslev et al. (1988), restricts matrices A and B to be diagonal. By doing so, the number of parameters needing estimation is reduced to 9. While the diagonal VECH GARCH model provides essential information for this research, it comes with a drawback; there is no assurance of a positive semi-definite covariance matrix (Alexander, 2001). It is important to note that a variance-covariance or correlation matrix must always be positive semi-definite (Brooks, 2008).

The second approach to estimating a time-varying hedge ratio involves employing a Rolling Window OLS model. This method finds diverse applications, as discussed by Myers and Thompson (1989) and Baillie and Myers (1991). Lien and Tse (2002), in their pursuit of estimating a minimum variance hedge ratio, employed a day-by-day rollover of the OLS hedge ratio, augmenting the next observation while dropping off the first one. In this research, three different windows are explored: a year window, a 6-month window, and a 3-month window. After evaluating their performance, the 6-month window yielded the most favorable results, prompting its adoption in this study. The selection criterion for the appropriate window was based on the R^2 of each rolling OLS, where the R^2 in the Rolling Window OLS method serves as an indicator of the hedging effectiveness of the estimated time-varying hedge ratio.

Subsequently, this study aims to assess and compare the hedging effectiveness of each type of hedge ratio to determine the most suitable method for estimating a minimum variance hedge ratio in the freight market. To achieve this, a portfolio is constructed based on the estimated hedge ratio, and the variance of each portfolio is calculated. The optimal estimation method for the hedge ratio is identified by examining the portfolio that results in the most significant reduction in variance, compared to the unhedged portfolio.

4. Empirical results

After conducting the Augmented Dickey Fuller test, it is observed that the level series in both spot and future prices does not exhibit stationarity. Consequently, estimation proceeds of the first differences of the level series, which demonstrates stationarity.

Table 1 Augmented Dickey-Fuller tests for stationarity.

Augmented Dickey-Fuller test statistic-*Null Hypothesis: Level prices has a unit root*							
Spot Prices		**First Differences of Spot Prices**		**Future Prices**		**First Differences of Future Prices**	
t-Statistic	Test critical value:	t-Statistic	Test critical values:	t-Statistic	Test critical values:	t-Statistic	Test critical values:
-2.735007	5 % level -2.867536	12.27091	5 % level 2.867536	2.366291	5 % level 2.867830	10.73260	5 % level 2.867536

Past research made the assumption that, when spot and future prices are not cointegrated, the only appropriate hedge ratio is the one estimated through the OLS method. The investigation into the presence of a long-run relationship between spot and future prices is conducted through cointegration. Following the methodology proposed by Engle and Granger (1987), examining two time series for cointegration requires that both series be stationary and possess the same degree of integration. In this case, both time series are integrated of order one, fulfilling the necessary hypotheses for conducting cointegration tests. To pursue this, the Schwarz criterion is employed, with the null hypothesis being the absence of cointegration.

Table 2 Cointegration test between spot and FFA prices.

Series: ΔF_t, ΔS_t				
Null hypothesis: Series are not cointegrated				
Variables	**t-statistic**	**Prob.***	**z-statistic**	**Prob.***
ΔS_t	-15.94816	0.0000	-1431.919	0.0000
ΔF_t	-15.39716	0.0000	-888.0396	0.0000

The critical values lead to a rejection of the null hypothesis, indicating that FFA and spot prices time series are cointegrated.

4.1 Hedge ratio estimation

As previously mentioned, the estimation of two distinct types of hedge ratios is undertaken to assess the hedging efficiency across different methodologies. The first type is the static hedge ratio, determined through two methods. The initial approach involves OLS, where the slope of the linear equation between the first differences of FFAs and spot prices is estimated. The second method employs an ECM to estimate the covariance between the first differences FFA and spot prices.

The static hedge ratio using OLS method, as already analyzed in methodology section, is the slope b of the linear equation between the first differences of spot and FFA prices.

$$\Delta S_t = a + b \cdot \Delta F_t + \varepsilon_t$$

The estimation of the above model provides $b = 0.166$, which is statistically significant, without any problems of heteroskedasticity or autocorrelation.

The static hedge ratio estimated through the ECM is calculated as $h_{ECM} = \frac{\sigma_{SF}}{\sigma_F^2}$, where σ_{SF} represents the covariance between spot and future prices, and σ_F^2 is the variance of future prices. The ECM variance-covariance matrix yields values of $\sigma_{SF} = 0.313$ and $\sigma_F^2 = 1.868$. Consequently, the hedge ratio obtained through ECM is $h_{ECM} = 0.168$.

Table 3 Static Hedge Ratio estimation.

Method	Estimated Hedge Ratio
Ordinary Least Squares (OLS)	0.166
Error Correction Model (ECM)	0.168

The second type of hedge ratio is the Time-Varying Hedge Ratio, and its estimation involves the utilization of two different methods as well. The first method employs GARCH models, as outlined in the methodology section.

The estimated hedge ratio is calculated by $h_t = \frac{Cov(S_t,F_t)}{Var(F_t)}$, where $Cov(S_t, F_t)$ is the covariance between spot and FFA prices, and $Var(F_t)$ is the variance of FFA prices. Both of these are time varying, and estimated by the VECH GARCH model. **Figure 1** represents the hedge ratio estimated by this method over time.

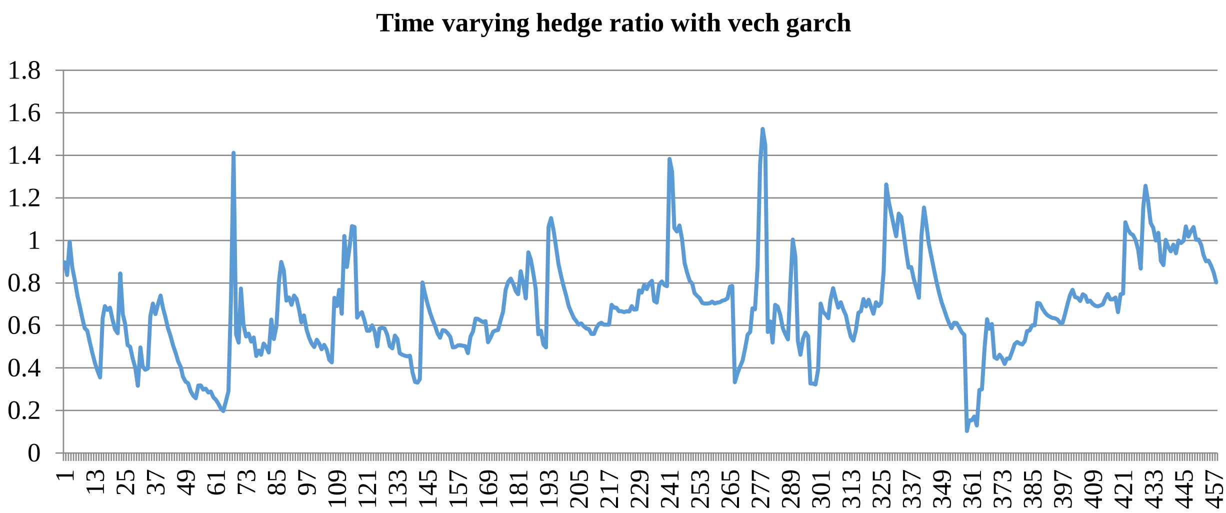

Figure 1 Time Varying Hedge ratio estimated with VECH GARCH.

The second method introduces a novel approach to the freight market research, utilizing a RW-OLS with a 6-month window. This method represents a new perspective in freight market analysis, as far as the author's current knowledge extends.

To derive a time-varying hedge ratio using the OLS method, the concept of a Rolling Window is employed, where each iteration involves adding one more observation and dropping the first one. Three different window lengths are experimented with: 3 months, 6 months, and 1 year. Following the criteria established by Myers and Thompson (1989) and Baillie and Myers (1991), the 6-month window is chosen, as it produced the most favorable results. The selection criterion was based on the R square from each regression.

The estimated hedge ratio obtained through the Rolling Window OLS is inherently a time-varying hedge ratio, and its dynamic changes over time are illustrated in **Figure 2**.

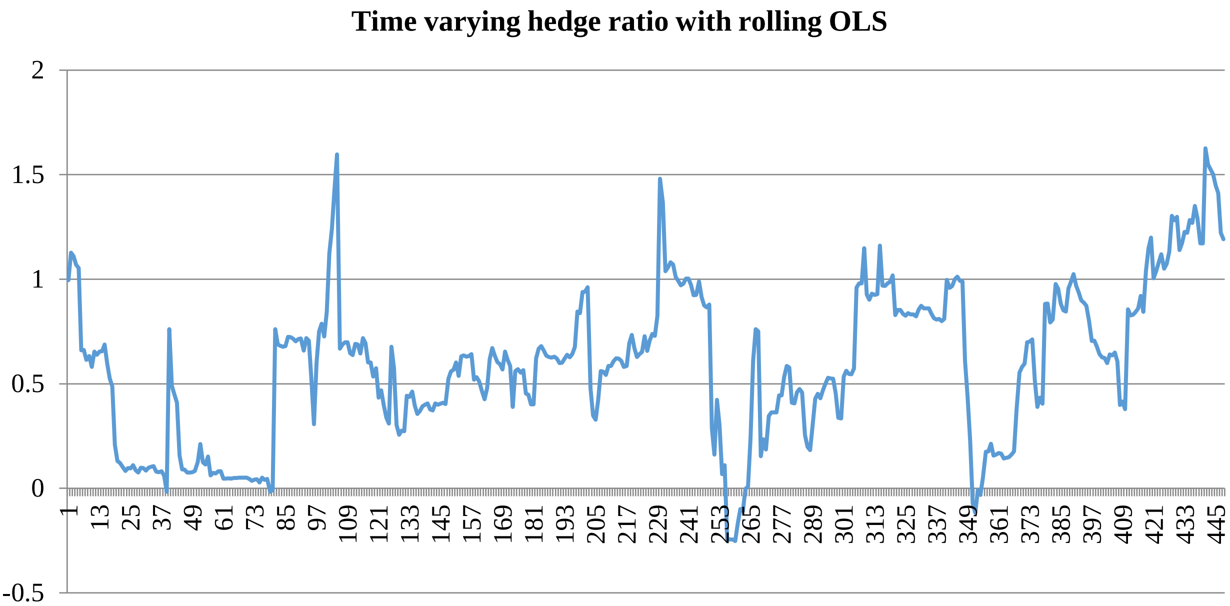

Figure 2 Time Varying Hedge ratio estimated with Rolling Window OLS.

The time-varying hedge ratios, estimated using two different methods, regarding **Figure 3**, appear to exhibit similar trends in certain time intervals, while in others, they diverge significantly.

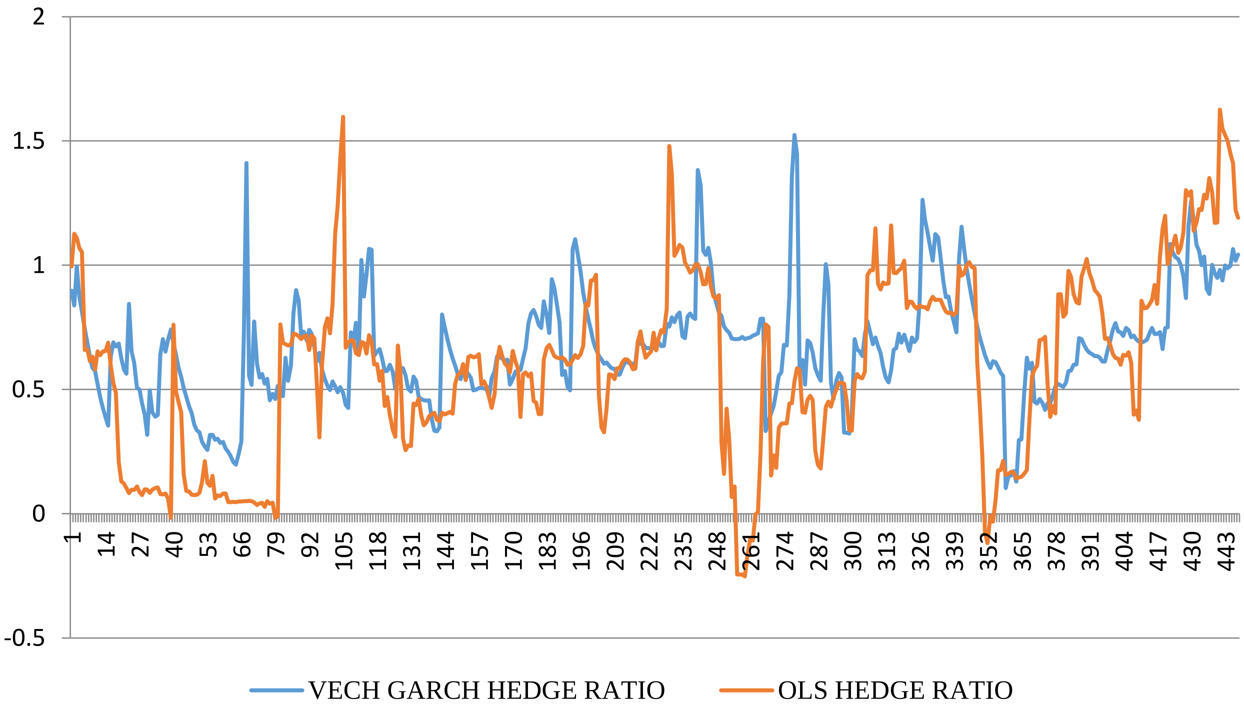

Figure 3 Time evolution of time varying hedge ratios estimated with VECH GARCH and Rolling Window OLS.

4.2 Hedging effectiveness

In assessing the hedging effectiveness of the various hedge ratios estimated through the different methods (OLS, ECM, diag. VECH GARCH, RW-OLS), a portfolio whose return is determined by the following equation is considered:

$$\Delta S_t - h \cdot \Delta F_t.$$

Subsequently, the variance of the portfolio is calculated under three distinct scenarios: a) the portfolio without hedging (h = 0), b) the portfolio with a hedge ratio of h = 1 (naive portfolio), and c) the portfolio with hedge ratios estimated by each of the aforementioned methods. Following this, the change in variance in each case is evaluated, and the optimal hedge ratio is identified as the one that attains the maximum negative change in variance.

Table 4 Hedging effectiveness tests.

	Mean	**Variances**	**Change**
Unhedged	12.926	9.73	
Hedged			
OLS	30.50	8.27	-63.95 %
ECM	29.93	8.20	-63.56 %
VECH GARCH	22.57	8.23	-51.50 %
R.W.OLS	43.17	9.81	-69.77 %
Naïve	4.87	3.40	-7.09 %

The results indicate that the RW-OLS method is the most suitable approach for estimating a hedge ratio in the freight market using FFAs. This method, producing a time-varying hedge ratio, achieves the maximum reduction in variance. The decrease in variance directly translates into a reduction of risk in the freight market.

4.3 Valuation of risk hedging using time charter

Time chartering has long been a conventional method for risk management, and has demonstrated effectiveness. In this study, this study aims to assess the hedging effectiveness of time charters and make a comparative analysis with hedging through FFAs.

However, a significant challenge arises in comparing the two hedging methods. The time series used for hedge ratio estimation, both for spot and FFA prices, were measured in \$/ton. In contrast, the time charter series, while representing the same route and period, were measured in \$/day. This incongruity in units makes a direct comparison of results unfeasible.

The issue is addressed by utilizing the Coefficient of Variation (CV), calculated as:

$$CV = \frac{st.deviation}{|arithmetic\ mean|}.$$

The Coefficient of Variation is a statistical measure that expresses the ratio of the standard deviation to the mean. It serves as a valuable statistic for comparing the degree of variation between different data series, facilitating comparisons even when the means of the series are significantly different from each other.

Then, the same portfolios as before with returns $S_t - h \cdot F_t$, where S_t represents spot prices, F_t represents FFA prices, and h is the hedge ratio estimated using the previous methods (OLS, ECM, diag. VECH GARCH, RW-OLS), are considered. All comparisons are conducted against the unhedged portfolio $h = 0$. Based on the unhedged portfolio, the reduction achievable in each case are measured. To include time charters in the comparison, the Coefficient of Variation (CV) are estimated and the reduction in CV is gauged.

Table 5 Hedging effectiveness tests.

	Mean	STDEV	CV	CHANGE
Unhedged	12.93	9.722918	0.752176	
Hedged				
OLS	30.50	8.270142	0.271131	-63.95 %
ECM	29.93	8.203518	0.274089	-63.56 %
VECH GARCH	22.57	8.232597	0.364781	-51.50 %
R.W.OLS	43.17	9.81536	0.227378	-69.77 %
Naïve	4.87	3.40326	0.698821	-7.09 %
Time Charter	20.650	13,032.06	0.631081	-16.10 %

The aforementioned results affirm that employing derivatives is significantly more effective in risk management compared to the traditional method of hedging against freight volatility, represented by time chartering

5. Conclusions

The primary objective of this study is to mitigate basis risk through the implementation of a dynamic hedging model tailored for shipping freight markets characterized by extreme volatility. The minimum variance hedging rule serves as the primary criterion for evaluating the effectiveness of various methods in estimating optimal hedge ratios. Additionally, by utilizing the coefficient of variation, this study aims to compare it with the hedging effectiveness of the traditional method, time chartering.

One notable result from this study is that the time-varying hedge ratio strategy has shown an improvement in reducing portfolio variance, compared to portfolios employing static hedge ratios and a naive approach. However, the observed improvement is marginal, ranging from a variance reduction of 51.50 % to nearly 64 %, depending on the estimation method. This finding aligns with similar studies, such as Kavussanos and Visvikis (2010), which utilized the same estimation methods. Notably, among the common methods, including OLS, ECM, and GARCH family models, the static methods (OLS and ECM) yielded the best results. This suggests that the incremental improvement in portfolio returns may not justify the use of a dynamic strategy, considering its complexity in numerically estimating conditional variances and covariances with a large number of parameters.

Additionally, in line with findings from other studies (Alexandridis et al., 2017; Adland & Jia, 2017; Kavussanos & Nomikos, 2000; Kavussanos & Visvikis, 2010), it is recognized that different GARCH models may yield diverse hedge ratio estimations across various routes. This necessitates a significant investment of time and resources to determine which model provides the maximum variance reduction. Moreover, in this study, the hedge ratio estimated using the GARCH model produces the least favorable result compared to other methods.

The most effective method for estimating the optimal hedge ratio is found to be the Rolling Window OLS. This method, widely applied in electricity markets, securities markets, and stock markets, has demonstrated superior results in hedging effectiveness, compared to complex GARCH models, in many studies.

To the best of the author's knowledge, this study represents the first application of the Rolling Window OLS method in estimating optimal hedge ratios within shipping freight markets. The variance reduction achieved through the estimated hedge ratio of R.W. OLS is approximately 70 %. This outcome aligns with the findings of Alexander and Barbosa (2007), who concluded that there is no evidence that complex econometric models can outperform an OLS regression in estimating optimal hedge ratios. Furthermore, this study's results are consistent with other studies (Adland & Alizadeh, 2018; Gupta & Singh, 2009) supporting the notion that simpler hedging strategies, utilizing straightforward methods like an OLS regression model, exhibit higher effectiveness, compared to more complex approaches in commodity markets.

In conclusion, another significant finding of this research is the poor hedging performance of T/C contracts, with a Coefficient of Variation reduction falling below 20 %. This insight is valuable for market participants, suggesting that time chartering may not be an effective strategy for risk hedging but could be explored for alternative purposes.

Additionally, the study highlights that freight derivatives do not achieve as high hedging performance as other commodity derivatives. The complexity of the shipping freight market, with its multitude of routes and commodities, may contribute to this outcome.

Market participants can derive practical insights from this study by estimating optimal hedge ratios to efficiently manage freight rate risk. The key result emphasizes the opportunity for shipping market participants to employ the Rolling Window OLS method, offering simplicity akin to the OLS method, but with the added inclusion of the crucial time-varying factor relevant to all financial time series. Future research will explore the application of this methodology in different shipping routes.

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