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A Dynamic Approach to Fuel Hedging with Reference to the 2020 International Maritime Organization Regulations

Bachelor's thesis

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Declaration of Authorship

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Abstract

In this thesis, we examine how marine fuels could be used in asset allocation with respect to portfolio management in a multivariate modelling and cross-hedging framework. The territory that remains largely unexplored is the level of interdependence between bunker spot and five most actively traded energy futures contracts. This approach relies on the (A)DCC-GARCH models as a workhorse of financial applications. We investigate whether all correlations and volatilities show asymmetry of responses to positive and negative innovations during both normal and turbulent periods and whether patterns of correlations could be traced across the global ports. In doing so, time-varying conditional variance-covariance matrices estimated from these models are used in calculating the optimal portfolio design. The analysis works as an umbrella term for the IMO 2020 sulphur cap regulations concerning oil refineries, marine industry and energy investors. Overall, this study has four main findings. Joint dynamics between return series matches overly volatile correlations with weak and positive links between commodities. Employing four different hedging rules and performing a rolling window operation, we find that complex hedging strategies do not provide greater benefits in reducing portfolio variance contrary to the static methods. Gasoil is the universal hedging instrument to manage uncertainty. In the present state of arts, heavy-sulphur fuel oils along with scrubber-fitted vessels are a better option to comply with sulphur content limits.

JEL Classification	C32, C58, G11, G15, Q02
Keywords	dynamic conditional correlations, hedging strategy, fuels, IMO 2020

Title	A Dynamic Approach to Fuel Hedging with Reference to the 2020 International Maritime Organization Regulations

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Abstrakt

V této práci se zaměřujeme na speciální případ rozdělení aktiv v námořní dopravě v rámci správy portfolia založenou na postupech ekonometrického modelování více proměnných a cross-hedgingu. Oblastí, která je v tomto smyslu z velké části neprozkoumaná, je vzájemná provázanost spotových cen paliv v dopravě a pěti nejlikvidnějších futures kontraktů. Pro tyto účely jsou v pojednání zastoupené modely typu (A)DCC-GARCH jakožto jedny z hlavních srovnávacích kritérií ve financích. Zkoumáme, zda korelace a volatilita jednotlivých kontraktů vykazují asymetrii ve vztahu k pozitivním a negativním novým informacím za krizových i normálních podmínek na finančních trzích. Snažíme se ukázat, jestli obraz korelací může být dostatečně zobecněn napříč čtyřmi světovými přístavy. Přitom odhadujeme časově proměnné podmíněné variančně-kovarianční matice, pomocí nichž měříme optimální portfolio. Tento rozbor je zároveň jakousi zastřešující analýzou pro opatření IMO 2020, zpřísňující množství síry v lodním palivu, týkající se zejména ropných rafinérií, námořního průmyslu a investorů v energetickém sektoru. Výsledkem této studie jsou čtyři následující závěry. Společná dynamika výnosů se shoduje s příliš nestálými, nevýraznými a nezápornými korelacemi mezi komoditami. Přicházíme s poznatkem, že komplexní hedgingové strategie oproti konstantním metodám neposkytují větší míru minimalizace rizika na základě rolování odhadů a čtyř různých hedgingových poměrů. Motorová nafta je nejlepším hedgingovým nástrojem nehledě na lokalitu. S ohledem na výzkum se dosavadní paliva s vyšším podílem síry v kombinaci se speciálním čisticím systémem jeví jako lepší volba v kontextu dodržení limitů pro emise síry.

Klasifikace JEL	C32, C58, G11, G15, Q02
Klíčová slova	dynamické podmíněné korelace, hedgingová strategie, paliva, IMO 2020
Název práce	Dynamický přístup k hedgování paliv s odkazem na nařízení Mezinárodní námořní organizace v roce 2020

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Acronyms

ADCC Asymmetric Dynamic Conditional Correlations

ADF Augmented Dickey-Fuller Test

ARA Amsterdam-Rotterdam-Antwerp

ARCH Autoregressive Conditional Heteroskedasticity

ARMA Autoregressive–Moving-Average

BEKK Baba-Engle-Kraft-Kroner

BG Breusch-Godfrey Test

BIC Bayesian Information Criterion

BP Breusch-Pagan Test

CCC Constant Conditional Correlations

cDCC Corrected Dynamic Conditional Correlations

CME Chicago Mercantile Exchange

COVID-19 Coronavirus Disease 2019

DCC Dynamic Conditional Correlations

ECA Emission Control Areas

ECM Error Correction Model

EIA Energy Information Administration

FFA Forward Freight Agreement

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GJR Glosten-Jagannathan-Runkle

GFC Global Financial Crisis

HEI Hedging Effectiveness Index

HSFO High-Sulphur Fuel Oil

ICE Intercontinental Exchange

IFO Intermediate Fuel Oil

IMO International Maritime Organization

JB Jarque-Bera Test

KPSS Kwiatkowski-Phillips-Schmidt-Shin Test

LM Lagrange Multiplier Test

LNG Liquefied Natural Gas

LPG Liquefied Petroleum Gas

LSFO Low-Sulphur Fuel Oil

MARPOL Marine Pollution Convention

MGARCH Multivariate Generalized Autoregressive Conditional Heteroskedasticity

MGO Marine Gasoil

MVHR Minimum Variance Hedge Ratio

n-ECA non-Emission Control Areas

NYMEX New York Mercantile Exchange

OHR Optimal Hedge Ratio

OLS Ordinary Least Squares

PPMMCC Pearson Product-Moment Correlation Coefficient

RBOB Reformulated Blendstock for Oxygenate Blending

ULSD Ultra Low Sulphur Diesel

ULSFO Ultra-Low-Sulphur Fuel Oil

VCM Variance-Covariance Matrix

VEC Vector Error Correction

VLSFO Very-Low-Sulphur Fuel Oil

WTI West Texas Intermediate

Bachelor's Thesis Proposal

Author	Michal Zítek
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Proposed topic	A Dynamic Approach to Fuel Hedging with Reference to the 2020 International Maritime Organization Regulations

Research question and motivation

This thesis sheds light on the volatility dynamics of spot and futures fuel prices as the optimal cross-hedging instrument, following highly anticipated 2020 International Maritime Organization Regulations (IMO 2020).

IMO has decided to implement a global 0.5% sulphur cap (currently 3.5%) for shipping fuel, coming into force on January 1, 2020. It is widely regarded as one of the biggest challenges and the most impactful changes to the oil industry in the last three decades due to its global and instantaneous effect. In consequence, shipping, aviation, and energy firms are currently revisiting the hedging aspects on IMO 2020. The potential shortage of compliant fuel induces companies to find other alternatives to bridge the gap. As a matter of fact, fuel prices across the whole energy complex are set to be substantially affected, well beyond marine fuel. There will be significant run cuts at refineries. The primary replacement is generally expected to be middle distillates, either diesel or gasoil; while the gasoline market is going to be challenged. Some other refined products, such as heating oil, may also be temporarily used to blend with non-compliant bunker fuel.

As the uncertainty in the prices of energy commodities arises, their futures price dynamics is of broad and current interest to energy investors and policymakers, not to mention the intense study of the academia in recent times. The focus on portfolio formations to manage companies' exposure to risk is important because it allows shielding investment in case of unpredictable swings in fuel prices, oil price shocks, capacity decline, or market turmoil as such. Hence, the optimality is associated with the least variability in returns. For that reason, price dynamics, evolution and the relationship between other commodities have major implications for entities that are subject to fuel price fluctuations. Multivariate generalized autoregressive conditional heteroskedasticity models (MGARCH) have long been used in such research on financial markets. Correspondingly, dynamic conditional correlations have been applied to capture commodity price volatility, and by extension, to mitigate price risk.

Contribution

According to oil analysts, the first stages of the sulphur cap will reverberate in the entire energy sector. The market is preparing for the transition and its overhaul is thus necessary. The expected contribution is threefold. As far as I am concerned, even though there is a rich array of literature on petroleum spot and futures volatilities, the comovements between gasoil and RBOB (reformulated) gasoline have not been inspected till now. In order to examine the hedging effectiveness, numerous studies (e.g. Pan et al., 2014) also reported conventional gasoline rather than the reformulated one. Its role has been neglected, but it is largely used for fuel proxy hedging.

Secondly, employing the seminal works of Engle (2002), Cappiello et al. (2006), and Aielli (2013), I will analyse the (a)symmetry in returns of petroleum-refined products, which is fundamental to risk management, investment, and regulatory policies. The use of Corrected Dynamic Conditional Correlation GARCH (cDCC-GARCH) and its asymmetric counterpart is yet to be explored under these conditions. This model should yield the best result in case of sudden and large changes in volatilities (Caporin and McAleer, 2014; Khalfaoui et al., 2012). The critical discussion of each method will be presented in terms of suitability, accounting for the models' strengths and weaknesses. Eventually, considering the cross-correlation of respective spot and futures contracts, and thereby the time-dependent optimal hedge ratio, I propose a sound (dynamic) fuel hedging strategy in the times of unexpected price fluctuations in a sense of higher hedging effectiveness and larger risk reduction.

Methodology

Hedging evaluation techniques will be constructed based on the extent of interconnection between spot and futures prices. Fuel hedging, be it diesel fuel, bunker fuel, or jet fuel, typically consists of three futures contracts – RBOB Gasoline, ULSD (heating oil), and gasoil. The estimation of the models will be conducted using daily data covering the period from April 1, 2006, until preferably January 2020. The data will be obtained from the Intercontinental Exchange (ICE) and the U.S. Energy Information Administration (EIA).

Upon understanding the aspects of the MGARCH models and the parsimony of parametrization, the DCC-GARCH family are to be used to capture necessary correlations. Owing to the fact that the difference between commodities may also accumulate over time, it is crucial to consider observations over an adequately long period. This is to effectively evaluate the differences between individual models regarding their dynamic conditional correlation estimates. Considering the problems and remedies of the DCC-GARCH, albeit not all of them, I will use more tractable alternative in Corrected DCC of Aielli (2013). Furthermore, its asymmetric version (Glosten, Jagannathan and Runkle-GARCH; cDCC-GJR) as developed by Cappiello et al. (2006) will be employed for the purpose of the robustness check as well as the introduction of conditional asymmetries in variances. By virtue of this, I investigate the asymmetric properties of the three energy commodities returns.

Thereafter, the time-varying conditional covariance matrices estimated from the aforementioned models will be used in calculating the optimal portfolio design, i.e. weights and hedge ratios on petroleum-based product returns. The risk reduction effectiveness indicator and the hedge effectiveness index will also serve us as a criterion to identify the (best) hedging performance, depending on GARCH type models, naïve strategy and a rolling window OLS. Finally, in-sample and out-of-sample testing will be formally assessed with the latter being more significant because of people's concerns about the future. This approach will be critical in testing the following hypotheses.

Hypotheses

Hypothesis #1: As a result of a sharp rise and fall in prices, there is heterogeneity in returns of petroleum-refined products.

Hypothesis #2: The rising correlations between gasoil, gasoline, and heating oil indicate a recessionary phase.

Hypothesis #3: The variance-covariance structure estimated from the Asymmetric (Corrected) DCC-GARCH provides the superior hedging potential.

Hypothesis #4: The best hedging performance can be achieved using gasoline and heating oil, implying the relevance of their joint production and closer application.

Outline

1. Introduction
2. Theoretical background and literature overview
3. Methodology
4. Data description

5. Empirical analysis and discussion of results, comparison with previous findings

6. Conclusion and future direction for research

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Author Supervisor

Chapter 1

Introduction

> *"To avoid all risks would be impossible; it might entail no flying, no driving, no walking, eating and drinking only healthy foods and never being touched by sunshine. Even a bath could be dangerous.* [...] *Optimal behavior takes risks that are worthwhile. This is the central paradigm of finance; we must take risks to achieve rewards . . . "*
>
> — Engle (2004)

Higher moments of economic random variables are determinants of many decisions related to the finance industry. Their dynamics have long been a fruitful area of research with many important implications for both academics and practitioners. Volatility and correlation modelling is thus of great importance to quantify risk stemming from economic, financial and insurance applications. Taking risks to achieve rewards is a trade-off which all market participants indulge in to some degree. Speculators bet on the prospective directions of the underlying asset value, adding liquidity to the market. Arbitrageurs simultaneously take positions in two or more instruments to secure a riskless profit. Hedgers are then the real commodity holders whose aim is to reduce their exposure to risk associated with market uncertainty. One of the most effective hedging instruments are futures contracts that also provide price discovery mechanism. Adverse price changes in the spot market might be, to a certain extent, offset by locking in a favorable price movement for the same (or another) commodity in the futures market. In the last two decades, energy futures overall have gained the pre-eminent place among international investors due to the progressive liberalization of financial markets, improvements in information transmission and innovations in market trading tools.

More than 80% of internationally traded goods are carried by marine vessels (Walsh et al., 2019). Although there are countless ports and marinas, the number of megahubs associated with international trade is low and they cover the greatest bulk of physical bunkering activities in the world – Rotterdam, Singapore, Fujairah and Houston. Bunker fuel is a historical term for fuels used in shipping and marine sectors. Stefanakos and Schinas (2014) suggest further investigations into bunker prices as shipowners, ship operators and charterers are confronted with high risks arising from price fluctuations. They argue that demand is quite inelastic as there are not many alternatives, and that supply depends on crude oil and refining capacity intertwined with environmental issues.

It has been widely documented that shipping is one of the main contributors to air pollution, be it sulphur oxides (SO_X), nitrogen oxides (NO_X), carbon dioxide (CO_2) or particulate matters. Both public health and environment are thus substantially impacted. As a consequence, there are a good many companies which are responsible for regulating emission standards. International Maritime Organization (IMO) is a specialized agency of the United Nations responsible for safety, security and ecological protection measures of shipping on a global scale. They issued the IMO 2020 new fuel regulations that entered into force on January 1, 2020, with the intention to reduce the emission of sulphur dioxide to 0.5% from the current level of 3.5% in non-Emission Control Areas (n-ECA). The IMO 2020 is an imminent and strenuous directive, and for its magnitude and urgency, it is thought to be one of the major challenges in the modern era. Not only do the environmental restrictions affect the marine and shipping industry, but also other energy segments, redefining crude oil market dynamics in general. They pose a challenge to producers, physical traders as well as refining and oil companies.

The objective of this thesis is threefold. An overarching concept is the use of financial derivatives as a measure against fuel price fluctuations. First, we investigate whether all correlations and volatilities show asymmetry and how similar patterns of correlations are across the continents. The intrinsic properties of fuels are also inspected. Second, we evaluate the cross-hedging of commodities with the intention to find the optimal hedging instrument. Alternative strategies are compared via in- and out-of-sample hedging performances, allowing for new market information arrival and its flexible adjustment. The results could be thus properly generalized. Third, conceiving of IMO 2020 as a transition to greener fuel, three practical scenarios for compliance have been formulated in practice. We endeavour to detect the most feasible solution accounting for strengths, weaknesses and suitability of each method.

On the basis of the above facts, our paper differentiates from the principal studies of Alizadeh et al. (2004) and Abadie et al. (2017) by a direct application of multivariate models and the use of commodities that have not been inspected till now. To remain in compliance with the IMO 2020 mandate, we analyze correlations between futures contracts and two types of bunker fuels, heavy and low sulphur fuel oils, following Panasiuk and Turkina (2015), Chu-Van et al. (2019), and Zhu et al. (2020). This is a refinement to previous approaches as our sample is updated to reflect more recent events and is sufficiently rich to meet the requirements of the models used for capturing conditional correlations (Engle, 2002, and Cappiello et al., 2006).

The paper documents that heavy sulphur fuel oils with scrubbers could be a better choice to comply with the new regulations. The intricacy of the topic lies in a particular interconnectedness of commodity markets. With its knowledge, the aforesaid models allow us to conduct different procedures, thereby identifying an attractive way to deal with the sulphur cap. The degree of correlations with futures contracts is usually higher around $20\% - 30\%$ in contrast to $10\% - 20\%$ of low sulphur alternatives with the exception of Rotterdam. Additionally, hedge ratios and a variance reduction technique incline towards the former approach. Our results also indicate that gasoil should be used for hedging purposes in the bunker industry notwithstanding local conditions in different ports. In general, the static OLS method is able to outperform more complex, dynamic models in terms of hedging effectiveness. On the contrary, these models should be used for detecting correlations, be it symmetric or asymmetric, as they can formally treat heteroskedasticity in our data.

The remainder of this thesis is structured as follows. Chapter 2 provides an overview of the relevant literature along with theoretical underpinnings. We proceed with setting the hypotheses and their development in Chapter 3. Chapter 4 is reserved for the methodological framework. Chapter 5 describes the institutional background and data, and gives a summary of the descriptive statistics for the markets and periods examined. Chapter 6 outlines the empirical results and provides a discussion on the portfolio management strategies. A robustness check for our empirical findings is presented in this section too. Finally, Chapter 7 offers concluding remarks and highlights policy implications. We also identify points that deserve further investigation and likely directions for future research.

Chapter 2

Theoretical background and literature overview

This chapter serves as an overview of the existing literature focusing primarily on energy market correlations and their use for investment and management decisions within the context of international regulations. There are specific theoretical aspects that need to be tackled upon prior both methodological and empirical parts to ease the complexity of building models and to have a complete picture of various concepts analysts work with. For the sake of simplicity, the chapter is divided into three parts, each concentrating on one aim of this thesis.

Before embarking on applied works, we formally assess volatility models with justification why the respective models are used later in the thesis. As bunker prices are intrinsically linked to crude oil prices, reflecting the supply and demand imbalances in the corresponding port and adjacent areas (Prokopczuk, 2011), this section also refers to crude oil comovements. Second, asset allocation literature attempts to address the risk-return characteristics of energy commodities. We also mention hedging in the marine sector, "a notoriously opaque segment of the oil market" (Halff et al., 2019), given its importance for the final hypothesis. Documented by more recent works on ship emission abatement systems, the last part is devoted to the Global Sulphur Cap 2020. However, the reported findings are somewhat conflicting in that there is no optimal solution. On the whole, in conjunction with Andersen et al. (2006), we use both aggregated (portfolio-level) and disaggregated (asset-level) modelling to explore the area of risk measurement as well as management.

2.1 Understanding financial correlations

Financial asset returns volatilities, (co)variances and correlations are critical inputs for many disciplines ranging from forecasting, hedging strategies, portfolio construction to asset pricing and optimization. Among other things, they help to shed light on various aspects pertaining to financial markets' performance, such as contagion effects, volatility spillovers and linkages across various markets and investment instruments. On that account, there is a handful of methods capable of modelling such relationships. The time-domain tools are, in particular, generalized autoregressive conditional heteroskedasticity models (GARCH), realized volatility and stochastic volatility. According to Caporin and McAleer (2014), the latter suffers from a computational burden the most and realized volatility usually requires high-frequency data; therefore, we resort to the former mechanism. It is the pioneering study of Engle (1982) where he proposes that the unobservable second moments can be modelled jointly with the first moments. Bollerslev (1986) later presents a generalized version of the model. The GARCH models are especially important since they are able to capture well-known stylized facts surrounding financial time series, such as leptokurticity, time-varying volatility with persistent dynamics or volatility clustering[1] (Cont, 2001).

Several extensions and generalizations of GARCH models have been proposed with different degrees of complexity and success in terms of application to real data. The notion of asymmetry is closely connected to the leverage effect phenomenon. This is the empirical fact that bad news (negative shocks) have a greater impact on volatility than good news (positive shocks) of the same absolute magnitude. Differing in their functional forms, the most popular univariate models that provide for an asymmetric function of the past data are the exponential GARCH of Nelson (1991); GJR-GARCH of Glosten, Jagannathan, and Runkle (1993); and Zakoïan's (1994) threshold GARCH model. Multivariate alternatives (MGARCH) are brought forward in much like the same manner. What is important for our thesis is that they usually display the greatest accuracy in modelling energy market volatility which is characterized by significant persistence and asymmetric effects (Wang and Wu, 2012). Aielli and Caporin (2014) and Caporin and McAleer (2014) argue that more sophisticated alternatives are generally preferred since they have statistically superior

1 Mandelbrot (1963) defines volatility clustering in asset returns as "large changes [that] tend to be followed by large changes, of either sign, and small changes by small changes."

performances during both market stress and calm periods. Whereas simple GARCH analysis can adequately trace dynamics of individual assets, they cannot capture the interrelationship either within or across several markets. A multivariate modelling framework can thus be regarded as more relevant for estimating asset return correlations conditional upon past information (Wang and Wu, 2012), particularly in terms of the energy market. They can effectively describe the joint distribution of spot and futures returns, which is the reason why this thesis employs these methods and scrutinize them in greater detail.

There is a wide stream of literature that covers the comparison of MGARCH models, repeatedly mentioning two seemingly incompatible features and that is "the curse of dimensionality" and "feasible model estimation" (Caporin and McAleer, 2014). The basic idea underlying these distinctive attributes is that the number of parameters to be estimated increases rapidly with the dimension, but realistic and parsimonious specifications of respective models may improve their tractability for a large number of assets. The latter should not lead to any arbitrary simplification purely because the relevant dynamics could be lost. Furthermore, there are three strands of the research, each of them investigating a certain area of quantitative disciplines, namely, parameterization, additional elements introduction, and alternative estimation techniques. It is worth noting that consistency issues and inherent features of univariate models are also pertinent to those multivariate ones. No exact statistical theory common to all of them has been formulated so far (Silvennoinen and Teräsvirta, 2009). The regularity conditions and asymptotic properties of the estimators, particularly with respect to maximum likelihood estimation, have not been fully explored and remain an open topic.

With the advent of the first multivariate GARCH model in the half-vec (*vech*) form that provides a general framework (Bollerslev et al., 1988), the number of studies on the quest for correlations increased substantially. Bauwens et al. (2006) classify these models into three categories. The first group covers direct generalizations of the univariate GARCH, and that is, VEC, its special case BEKK (due to the synthesized work of Baba, Engle, Kraft and Kroner as appeared in Engle and Kroner, 1995) and factor models,[2] including RiskMetrics. It should be noted that BEKK is one of the two most popular models that exploit standard comovement methodology. Its more tractable formulations have been devised, but still the interpretation is difficult to discern given

2 Factors are common underlying variables with a GARCH-type structure driving comovements of stock returns.

generality reduction and yet a high number of unknown parameters even in the trivariate case. Latent factor models and (generalized) orthogonal models fall under the second category. Finally, this thesis employs nonlinear combinations of the univariate GARCH that altogether consist of conditional correlations models, general dynamic covariances and copulas. Compared to the previous classes, they can be easily estimated with a clear inference procedure accounting for temporal variation in the conditional second moments. Primarily, both dynamic conditional correlation models of Engle (2002) and Tse and Tsui (2002) are appealing due to their flexibility as the number of parameters estimated in the correlation process does not depend on the number of series to be correlated.

While a significant body of literature has focused on volatility spillovers across different markets, our paper reserves solely to the energy financial market. Nonetheless, commodity prices retain extreme statistical properties, contrasting other financial assets such as debt securities and equities (Baruník and Vácha, 2012). Over the past two decades, there have been drastic price fluctuations of commodities, especially crude oil and its refined products which remain the backbone of many economies; for example, Saudi Arabia, Russia, Canada or the United States. Commodities' financialization coupled with the globalization of the commodity market, trade wars connected to the international rhetoric, and changes in industrial production and consumer sentiment have gathered considerable momentum with traders, investors, policymakers and researchers. In this spirit, Chang et al. (2006) examine several multivariate volatility models for the crude oil spot and futures returns of Brent and West Texas Intermediate (WTI). WTI has higher liquidity, is more expensive, and reduces the variance of portfolio by 24% more when compared to Brent specification. In addition, DCC models instruct to hold futures in larger proportions than spot. They conclude that diagonal BEKK is the most convenient model as for reducing the variance of the portfolio. Following a similar line of research, Baruník and Vácha (2012) employ the wavelet tool to study energy market dynamics in the time-frequency domain because the standard DCC is unable to decompose the spillover effect and comovements on various time scales. Natural gas is unrelated to WTI, heating oil or gasoline. Furthermore, the authors observe significant coherences of the three most correlated commodities for a large number of investment horizons, particularly amplified during the times of plunge in prices, pointing to a potentially well-diversified portfolio.

Numerous studies attest to the leverage effect and asymmetric responses to uncertainty in energy time series data. Baruník et al. (2015) explore asymmetries in volatility spillovers across petroleum markets using high-frequency data. They postulate that negative returns induce volatility spillovers to a greater degree than the positive ones. The dominant aspect of their study is that market turmoil does not prompt spillovers between WTI, gasoline or heating oil to be more volatile in any way. Radchenko (2005) examines the relationship between oil price volatility and the degree of asymmetry in gasoline prices, indicating their negative relation in that when the former increases, the latter proportionally declines. Using trivariate BEKK and DCC models, Efimova and Serletis (2014) show undirectional price spillovers between crude oil, natural gas and electricity, demonstrating the hierarchy from oil to gas and electricity with the correlations gradually decreasing during times of recession. They insist that abnormal dynamics in the market combined with the increase use of oil futures weakened the link between the other two commodities. As another example, Pan et al. (2014) suggest a more in-depth analysis using both weekly spot and futures contracts of WTI, conventional gasoline and heating oil. They combine the asymmetric time-varying correlations and a Markov regime switching method to learn that heating oil instead of gasoline is more appealing for refiners who cannot access the local crude oil futures market.

2.2 The case of hedging

This thesis stresses the importance of hedging the spot position with futures contracts, a portfolio theory first introduced by Johnson (1960) and Stein (1961). By hedging, companies shield their portfolios against potential adverse movements in the markets while not reducing the expected return. The counterargument might be that hedging is risky since market participants can end up with a worse outcome than with no hedging (Hull, 2014). The main strand of the literature focuses mainly on optimal hedging strategies; for instance, hedge ratios based on expected utility maximization, mean extended-Gini coefficient, value-at-risk, and generalized semivariance, with minimum variance hedge ratio (MVHR) being the most prevalent technique. This is the simplification of the expected utility maximization paradigm (Kroner and Sultan, 1993).

Previous authors have identified mainly three models that can be used in the minimization of the variance of the portfolio. First, the MVHR estimation is traditionally carried out via the linear ordinary least squares (OLS) regression (Ederington, 1979). Much effort has gone into what is the advantage over the static method of OLS since it neither allows for heteroskedasticity nor cointegration, which may lead to misspecification, and ultimately, unhedging. Myers and Thompson (1989) criticize this method on the grounds that it cannot capture the maximum information available when the hedging decision is made. Second, a more flexible mechanism that gives a satisfactory record of time-varying volatility in commodity prices should be formulated with GARCH-modelling as a starting point (Myers, 1991; or Adams and Gerner, 2012). Furthermore, Kroner and Sultan (1993) point to the intertemporal instability in the hedging effectiveness of conventional approaches, accentuating that the dynamic hedging strategy offsets the transaction costs for investors. Lien and Yang (2008) strongly endorse the dynamic hedging strategy while incorporating asymmetric basis effect into the hedging decision. This should provide more accurate descriptions of the joint behaviors of energy commodities prices and returns. Accordingly, the correlations between spot and futures contracts cannot be static, otherwise, this would lead to sub-optimal hedging decisions during high basis volatility and inefficient revisions of hedge ratio (Cifarelli, 2011). Overall, there is a consensus that the third commonly used technique, the error correction model (ECM), along with MGARCH models outperforms the static techniques.

On the other hand, further reasoning shows that more accurate volatility estimation does not always translate into better performance from the risk-minimizing standpoint beyond OLS (Ku et al., 2007; Ji and Fan, 2011). Lien et al. (2002) provide a discussion of the trade-off between the benefits of a dynamic hedge and the costs of portfolio rebalancing. To put it differently, the requirement of daily adjustments of the futures position brings with it additional computational costs. This view is supported by Lien (2009) who contends that GARCH-based models and random coefficient models produce excessively volatile MVHR, which leads to unnecessary transaction costs. Laws and Thompson (2005) attribute these clearly defined patterns to the type of hedge, the type of asset and a sample choice. In fact, the longer the duration of the hedge, the less beneficial the time-varying hedge is (Lin et al., 1994). It can thus be concluded that hedge ratios vary substantially across commodities. What is more, the empirical results of Chun et al. (2019) provide evidence that hedging risk altogether can be ineffective due to neglecting the regime shift periods in the oil market. Examining five structural breaks in the oil price – the Gulf War, the Asian financial crisis, the Iraq War, the global financial crisis, the shale gas boom – they contend the model parameters cannot be uniformly estimated during these episodic events. The hedge performance may thus be biased, distorting empirical results. Billio et al. (2018) propose Bayesian hedging on oil spot and futures markets before, during and after the 2007-2008 global financial crisis, stating the need for many different models to be used due to various phases of the market.

Motivated by either non-existence of a corresponding futures contract, researchers also look at the concept of cross-hedging, i. e. the asset allocation involving two different assets. As a practical matter, some papers use the term proxy and cross hedging interchangeably. Unlike currency hedging, there is no difference in terminology for commodity futures hedging. If there is no futures contract on the asset whose price is being hedged, then the hedger should choose similar asset underlying the futures contract. This is where the knowledge of correlations, though imperfect ones, becomes useful. The effectiveness of the futures market for cross hedging is first stressed in the influential paper of Ederington (1979) as a possible avenue for facilitating effective hedging.

Hedging crude oil using refined products is common to most of the studies as crude oil dominates the interaction with other markets. The number of papers on cross-product hedging in the energy market has expanded since the notable work of Wang and Wu (2012). They use weekly spot prices of conventional gasoline, heating oil and jet fuel as they stipulate that WTI futures should behave similarly to the underlying spot prices. Heating oil should be hedged against the price uncertainty of crude oil because of the highest hedging effectiveness and the utility function. Gasoline prices are even more volatile than crude oil prices, whereas jet fuel does not account for a great proportion of a barrel of crude unlike heating oil. Correspondingly, Lim and Turner (2016) address hedging performance of four jet fuel proxies by means of diagonal BEKK and CCC-GARCH. Heating oil is the most reliable cross hedge based on different hedge horizons and contract maturities with the weekly horizon and one and three-month contracts dominating the holdings. WTI is a more attractive commodity than Brent while gasoil performs the worst. Furthermore, they find that hedge effectiveness is location sensitive given the fact that jet fuel spot prices from the area of Amsterdam, Rotterdam and Antwerp (ARA) are more correlated with futures prices of gasoil that is likewise traded in Europe. Moreover, Ji and Fan (2011) study mutual relations among crude oil, gasoline and heating oil spot and futures prices to develop a multiproduct hedge on the basis of a spread as a representative measure of cracking profits. Crude oil is processed into downstream products via cracking. Spread then stands for the difference between the selling and purchasing price of futures contracts, therein crude oil and its refined products. CME (2017) presents a diversified 3:2:1 crack spread, i.e. three crude oil futures contracts versus two gasoline futures contracts and one heating oil futures contract. The authors employ the DCC-ECM-MGARCH to effectively avoid the double volatility risk. If the price fluctuates drastically, the static hedge model cannot reduce risk, but increases it instead. OLS is thus considered to be more suitable for relatively moderate market periods.

As a matter of fact, it is possible to use various financial derivatives for hedging in the shipping industry as shippers have locked in spreads, fixed-price swaps and forwards for quite some time. For example, Samitas and Tsakalos (2010) investigate the effectiveness of freight forward agreements (FFA) during financial crises and measure their impact on shipping firms' value. They can also provide substantial protection against risk exposure. Adland et al. (2020) put forward a similar point by arguing that the hedging efficiency is greater for newer vessels up to 15 years of age and that the static hedge ratio is better than the dynamic one when using FFAs. The dynamic interrelationship among the three related markets of crude oil futures, bunker futures and tanker derivatives is examined in the study of Sun et al. (2019). They give evidence of bidirectional behaviour in returns with Brent futures to be net information transmitter to the other markets and bunker futures to serve a buffering role.

While a considerable number of authors carry out empirical studies on hedging, there have been practically no studies published on bunker fuel hedging since the seminal work of Alizadeh et al. (2004) which serves as the main source of comparison for our thesis. They build on the paper of Menachov and Dicer (2001) who employ a VEC model with a GARCH error structure to document Rotterdam bunker fuel prices and gas and oil futures traded on ICE (the authors use International Petroleum Exchange notation; since April 30, 2001, these companies have been merged). This thesis aims to update and extend the approach of Alizadeh et al. (2004) who use weekly petroleum futures contracts in Rotterdam, Singapore and Houston, employing VECM and diagonal BEKK. The greatest variance reduction attained is 43% when using ICE Brent to hedge bunker prices in Rotterdam, which is insufficient in contrast to other markets. The single most appropriate futures contract in all three ports seems to be gasoil. As a whole, ICE futures contracts rather than NYMEX contracts provide superior hedging performance. Birkett (2019) asserts that one of the shipowners' options for IMO 2020 compliance is to hedge bunker prices using derivatives. However, it is reported that less than 1% of the global bunker market has been hedged for 2020 as a result of the lack of liquidity and transparency.

2.3 The IMO 2020 mandatory initiative

Cutting sulphur oxides to the maximum of 0.5% has been an issue for its urgency but also technological constraints for a considerable amount of time. To put it into context, one large container ship using bunker fuel with 3% sulphur content emits as much sulphur oxides as 50 million diesel-burning cars (IGU, 2017). Efforts to limit the harmful impact of ship emissions date back to 1973 when the Marine Pollution Convention (MARPOL) was adopted. IMO (2020) hopes for 77% drop in overall sulphur oxide emissions from ships. New stringent regulations create a multifaceted phenomenon since they affect the whole energy sector and paths to compliance are more complex than it seems. Not only is it expected that there will be upward price pressure in marine and bunker fuels, but also products ranging from naphtha to diesel and other middle distillates are likely to be impacted. As a consequence, inland distributors may also feel the impact no less than end-users. Many companies turned to a wait-and-see approach prior to the IMO 2020 launch, yet there was also a thorough preparation ahead of the regulatory shift. Several studies have examined novel deep desulphurization techniques; nonetheless, their suitability for the bunker industry is subject to further research. Our focus is laid on the three paths to compliance which are constantly being revisited to detect the most economically efficient candidate. The most appealing approach seems to be hard to find due to various factors outlined below.

The first method consists of installing scrubbers, an exhaust gas cleaning system that removes the sulphur from post-combustion exhaust emissions, in conjunction with the usage of heavy-sulphur fuel oils (HSFOs). Chu-Van et al. (2019) and Chu-Van et al. (2020) argue that the cost effectiveness of such approach is wide enough to offset both capital and opportunity costs. Analysing the investment efficiency evaluated by cash flow modelling, Panasiuk and Turkina (2015) advocate that the combination of scrubbers and residues of crude oil distillation help to reduce operating costs. On the other hand, there are numerous drawbacks, for instance, the reduction of cargo-carrying capacity, layup time during retrofitting, losing deck space, and installation and annual maintenance costs (Gu and Wallace, 2017, and Bergqvist et al., 2015). Furthermore, Williams (2010) points to the increased fuel consumption by 2% attributed to the supplementary engine as a trigger for high speed shipping operation and the release of greenhouse gas. Apart from that, the feasibility of using scrubbers varies from old to new ships. Jiang et al. (2014) find evidence that retrofitting an existing ship costs 40% more than installing it on a new ship. As a result, provided that the vessel's remaining lifespan is less than four years, it loses its attractiveness.

The second option to meet the low-sulphur requirements is to switch from HSFOs to low-sulphur fuel oils (LSFOs),[3] such as marine gasoil (MGO), marine diesel oil (MDO), very low-sulphur oil (VLSFO) and ultra low-sulphur oils (ULSFO). The sulphur content is 0.1%, 0.5% and 0.1% m/m (mass by mass), respectively. It is commonly believed to be the most likely path the market participants could take to satisfy the requirements, but envisaging it in its entirety is not feasible. The obvious advantages over the first scenario are initial installation and maintenance costs. Zhu et al. (2020) stress reliable and stable sources of information of MGO contrary to other types of LSFOs; and hence it is benchmarked against the very first option in our analysis as a representative of this scenario. They also point out to the higher price of LSFOs and higher operating costs, just as uncertainty in their supplying and lower sailing speed compared to HSFOs. Furthermore, Chu-Van et al. (2019) argue that MGO is not favourable in the long-run given an insufficient payback for the capital investment of its propulsion. On another note, lower-sulphur blends and marine distillates can also be regarded as a certain subcategory of compliant fuels. ULSD[4] and gasoil may be blended with residual fuel oil, creating a rather uncommon synthetic price market considering post-2020 expectations (Mladenik and Grimmer, 2019).

Conversion to alternative fuels is the third compliance path. Due to their infancy in ports and impossibility to combine them with old watercraft, they are not the object of this paper's interest but a brief delineation will be given. Moreover, it is the approach many studies take. Having said that, nonpetroleum-based fuels that meet the sulphur limits become very popular as they are increasingly abundant and poised to redefine the energy industry towards a

3 Low-sulphur oils are generally considered to contain 1% of sulphur, and thus do not comply with the IMO. However, for ease of reporting, the abbreviation LSFOs stands for fuels compliant with the regulations.

4 ULSD has 15 parts per millions (ppm) of sulphur, IMO 2020-compliant fuels have 5000 ppm, while conventional bunker fuels have 35000 ppm. The blend ratio could be 1000:1 for ULSD and bunker fuels, respectively (Pierce, 2018).

greener future. Ships can run on liquefied natural gas (LNG), liquefied petroleum gas (LPG), methanol, hydrogen, certain biofuels, or synthetically manufactured fuel oils (Lähteenmäki-Uutela et al., 2017, and Bergqvist et al., 2015, among all). Zhu et al. (2020) address the substantial up-front investments, limited port provision, and lower carrying capacity as major disadvantages. According to IMO (2016b), LNG remains an attractive tool to reduce air pollution despite its costs, including the price and liquefaction of natural gas, premium for transport and fuelling. What needs to be accentuated is that LNG-fuelled vessels need to carefully identify ports with adequate shoreside supply facilities for refueling since they are not available in minor ports (Fagerholt et al., 2015). Conversely, methanol has both lower investment and space requirement but its high fuel cost makes it marginal (IMO, 2016a). What is more, the shipping industry is still not inclined to switch to these alternatives given the estimated number of 200 vessels burning them out of a total oceangoing fleet of approximately 45 000 vessels, that is 0.44% (Halff et al., 2019). In the upshot, these are the reasons why we disregard this scenario.

Making a decision between scrubbers and LSFOs-switching is not an entirely recent conundrum. A close appraisal of the existing literature reveals that there are numerous approaches to at least partially solve the riddle. Zhu et al. (2020) use a cost-benefit analysis to arrive at the conclusion that the combination of heavy fuel oils and scrubbers is more economically efficient due to their declining prices and feasibility for both old and new ships, respectively, as opposed to the LSFOs' price surge and limited availability. As for the similar methodology, the identical results are found in the studies of Lindstad and Eskeland (2016) and Chu-Van et al. (2019). The authors also give cautionary advice about increasing fuel consumption, which naturally leads to greater emissions. Overcoming the drawbacks of the cost-benefit analysis by a generalized-decision making model, Ölçer and Ballini (2015) find clear evidence for scrubbers being the best compromise solution based on multiple attributes. They take into account capital cost, payback time, external cost, air pollution and noise, assigning each with a corresponding trapezoidal fuzzy number, and thereafter, constructing the decision matrices. In a different manner, Gu and Wallace (2017) propose a mathematical programming model, incorporating the optimization of ship's sailing pattern, such as route and a speed choice, into the assessment method. The scrubber system comes off as a winner for ships that have higher ECA port call density while fuel-switching is more attractive to shipping companies operating less in or outside these areas. Furthermore, Solakivi et al. (2019) use descriptive analysis and logistic regression to form a profile of vessels based on the abatement methods. Their study shows that vessels with scrubbers should operate in the ECA areas with the exception that MGO is the most cost effective option for ships with annual consumption of less than 1500 tons. Finally, Abadie et al. (2017) employ a stochastic diffusion model to estimate future marine fuel distributions derived from crude oil spot and futures prices and the differentials between crude oil and marine fuels. They conclude with the proposition that these prices, to some extent, can be hedged, arguing that the main factor for opting for either of the two scenarios is the remaining lifetime of a ship. The longer it is, the more appealing investing into scrubbers is. This is the only paper that elaborates on the strong correlations between crude oil and marine fuel prices. Nonetheless, these correlations are adopted as given from the Energy Information Administration (EIA) and Rotterdam ports. In the end, we try to cover all of the materials for deriving an optimal solution in a more robust way.

Chapter 3

Hypothesis development

This chapter is concerned with generating hypotheses as a building block for our econometric research. Motivated by some of the issues discussed in the previous section, we develop testable hypotheses by emphasizing key findings in the literature, making generalizations where necessary. It will be recalled that some of the hypotheses are, in fact, stylized facts that can be directly applied to the marine and shipping industry.

The commonly observed pattern on financial markets is that the continuous release of new information changes the economy insofar as the levels of economic and political stability naturally differ. This in turn affects supply, and thus prices of not only financial instruments. Therefore, the first hypothesis is an empirical matter that originates in tracing variations in volatility over the course of time.

> Hypothesis 1: As a result of a sharp rise and fall in prices, there is heterogeneity in returns of petroleum-refined products.

This criterion rests on the two asymmetric phenomena described in Pan et al. (2014). The first effect is defined in Chapter 1 and concerns different impacts of positive and negative innovations on volatility. They take the second asymmetric effect as a stylized fact. Specifically, the correlations between crude oil and its refined products vary during the periods of a price increase and decrease. That should be a fair expectation.

Next, we examine how the (a)symmetric linkages between energy commodities might indicate a certain phase of the market in general. The number of factors affecting the commodity market is high, such as growing renewable energy and biofuel demands, deregulation associated with electricity market, the regulations issued by the IMO, extreme weather events, or infectious disease outbreaks. Furthermore, consistent with the literature on the spot-futures relationship, Sarwar et al. (1999) claim that futures contracts might emphasize price fluctuations in the spot market, while the reverse link seems to be weak. It works like an echo in various forms, especially during and shortly after financial crisis periods rather than economic stability. Following the first hypothesis, we thus anticipate that

Hypothesis 2: The rising correlations between selected pairs of commodities indicate a recessionary phase.

Suffice it to say that the negative effect propagates through correlations more substantially than positive shocks. With this rationale, we may now turn to the portfolio management technique. That controlling for conditional heteroskedasticity improves hedging performance is supported by many studies (Lien and Yang, 2008, and Alizadeh et al., 2004, above all). As the patterns of price fluctuations change over time, the understanding of risk factors stemming from different market regimes is of great significance to guarantee a convenient risk-minimizing strategy. Zhao et al. (2019) assert that dynamic models are particularly useful in recognizing the tail features of financial time series and correlativity of spot and futures returns. To gain further insight, estimating optimal hedge ratios with more flexible patterns of persistence in the conditional covariance matrix leads to testing the third hypothesis.

Hypothesis 3: The variance-covariance structure estimated from the ADCC-GARCH provides the superior hedging potential.

Consequently, accounting for the asymmetric effect in the time path of the optimal hedge ratios, Chun et al. (2019) and Billio et al. (2018) postulate that joint dynamics between spot and futures markets can be captured to the presumably highest degree. This appealing result is justified on the grounds that uncertainty, yet again coming primarily from the spot market and being transmitted to the futures market, cannot be ignored (Meneu and Torró, 2003), even at a cost of portfolio rebalancing.

According to the above discussion mainly with respect to the theoretical design, the following hypothesis is formulated:

Hypothesis 4: Regardless of the port, the best hedging performance can be achieved using crude oil futures and intermediate fuel oil, implying the relevance of their joint production.

This hypothesis makes one crucial prediction. It implies that the first scenario is very likely to become prominent in the near future given how bunker spot prices are extremely volatile. Lay-ups during which ships berth in ports instead of operating in waters and capital investments in scrubbers are considered to be offset by favourable price comovements between the aforementioned commodities over a long-term horizon. Therefore, we predict that both WTI and Brent crude oil remains to be the excellent hedging instruments in portfolio risk mitigation on bunker markets. It is also argued that location sensitivity might not be the most important aspect in the context of the bunker industry because the crude oil dominance erases differences in specificity of commodities. This suggestion derives from the inherent relationship between oil-based and bunker products.

Chapter 4

Methodology

This chapter is structured in the order in which the respective methodological principles of financial econometrics appear in the empirical analysis. First, we provide an account of the conditional econometric models that can capture the second moment dynamics of asset returns in the manner of the GARCH processes. Thereafter, hedging strategies are introduced with the focus on various risk minimizing hedge ratios, both time-varying and time-invariant, using pairwise correlations as inputs. Specifically, we use the hedging effectiveness index that allows us to compare the competing models with the industry standard of the dynamic conditional correlations.

For the purpose of external validity of time series analysis, the concept of stationarity needs to be set forth. A stochastic process $\{r_t\}$ is *strictly stationary* if its probability distribution does not change over time, that is, the joint distribution of $(r_{k+1}, r_{k+2}, \ldots, r_{k+T})$ does not depend on k irrespective of the T value (Brooks, 2019). To put it more succinctly, stationarity ensures that history is relevant. The finance literature uses its weaker version commonly referred to as a *covariance-stationary* process if for $t = 1, \ldots, T$ and $s \neq 0$:

- $\mathbb{E}(r_t) = \mu$,
- $\mathbb{E}[(r_t - \mu)^2] = \text{var}(r_t) = \sigma_r^2$,
- $\mathbb{E}[(r_t - \mu)(r_{t-s} - \mu)] = \text{cov}(r_t, r_{t-s}) = \psi_s$.

Provided that these relationships hold, then the first and second unconditional moments and the (auto)covariances of a single return series are unaffected by a change of time origin. This will prove useful in subsequent applications, particularly, parameter estimation.

4.1 GARCH analysis

4.1.1 Univariate GARCH models

Since the correlation estimation requires modelling conditional variance, it is necessary to briefly describe univariate models first. Engle (1982) introduces a class of stochastic processes known as autoregressive conditional heteroskedasticity (ARCH) processes to provide an account of time-varying volatility. The advantage is in allowing the conditional variance h_t to depend on the elements of the information set as a linear function of the past squared residuals with the constant unconditional variance. It ought to be emphasized that the autoregressive–moving-average (ARMA) model with a correct order shall be fitted before estimating any ARCH. General ARMA(m,n)-ARCH(p) model is thus given as

$$\begin{aligned} r_t &= \psi_0 + \sum_{i=1}^{M} \psi_i r_{t-i} + \sum_{j=1}^{N} \phi_j \varepsilon_{t-j} + \varepsilon_t, \\ \varepsilon_t &= \sqrt{h_t} z_t; \quad z_t \sim N(0,1), \\ h_t &= \omega + \sum_{p=1}^{P} \alpha_p \varepsilon_{t-p}^2, \end{aligned} \tag{4.1}$$

where r_t are logarithmic returns, ε_t is a white noise process, and z_t is a sequence of independent and identically distributed (*iid*) random variables with zero mean and unit variance. The following parameter restrictions ensure a covariance stationary process with a positive conditional variance h_t at all times: $\omega > 0$, $\alpha_p \geq 0$ for $p = 1, 2, \ldots, P$; and $\sum_{p=1}^{P} \alpha_p \leq 1$. The parameter α_p governs the effect of a return shock p periods ago ($p \leq P$) on current volatility.

Bollerslev (1986) generalizes Engle's model to the GARCH(p,q) such that

$$h_t = \omega + \sum_{p=1}^{P} \alpha_p \varepsilon_{t-p}^2 + \sum_{q=1}^{Q} \beta_q h_{t-q}, \tag{4.2}$$

where $\alpha_1, \ldots, \alpha_p,\ \beta_1, \ldots, \beta_q,$ and ω are constant parameters. Again, to guarantee that the conditional variance is always positive, the following conditions need to be met: $\omega > 0$, $\alpha_p \geq 0$ for $p = 1, 2, \ldots, P$; $\beta_q \geq 0$ for $q = 1, 2, \ldots, Q$; and $\sum_{p=1}^{P} \alpha_p + \sum_{q=1}^{Q} \beta_q < 1$.

In line with the substantial empirical evidence, we will illustrate the baseline GARCH(1,1) model because it adequately captures the dynamics of the variance and facilitates rich interpretations that can be extended to various specifications. The computational burden is thus reduced as it provides a parsimonious description of our data. Accordingly, Equation 4.2 is simplified to

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}. \tag{4.3}$$

Comparing various GARCH modifications, Engle and Ng (1991) assert that the GJR-GARCH of Glosten et al. (1993) is the best parametric model out of all the specifications that emphasize the asymmetry of the volatility response to news. Their model is rich enough to capture that property and is empirically proven that it does well in both normal and abnormal times. They suggest augmenting Equation 4.2 with an additional term conditional on the sign of the past innovations given the fact that positive and negative unanticipated returns revise conditional volatility differently from one another.

$$\begin{gathered} h_t = \omega + \sum_{p=1}^{P} \alpha_p \varepsilon_{t-p}^2 + \sum_{o=1}^{O} \gamma_o \varepsilon_{t-o}^2 I_{t-o} + \sum_{q=1}^{Q} \beta_q h_{t-q}, \\ I_{t-o} = \begin{cases} 1 & \text{if } \varepsilon_{t-o} < 0, \\ 0 & \text{otherwise.} \end{cases} \end{gathered} \tag{4.4}$$

I_{t-o} is a dummy variable taking the value of one if the shock is negative. The parameter restrictions are given as follows: $\omega > 0$, $\alpha_p \geq 0$ for $p = 1, 2, \ldots, P$; $\beta_q \geq 0$ for $q = 1, 2, \ldots, Q$; $\alpha_p + \gamma_o \geq 0$ for $p = 1, 2, \ldots, P$ and $o = 1, 2, \ldots, O$; and $\sum_{p=1}^{P} \alpha_p + \frac{1}{2}\sum_{o=1}^{O} \gamma_o + \sum_{q=1}^{Q} \beta_q < 1$. The coefficient on the lagged error terms is then $\alpha_p + \gamma_o$. In case of the positive shock, it is only α_p. Therefore, the statistical significance of γ_o implies that the asymmetric effect occurs. If γ_o is negative and significant, negative shocks have a more pronounced effect in volatility than positive ones of the same magnitude. The reverse is true if γ_o is positive and significant.

The specification for the conditional variance of GJR-GARCH(1,1,1) reads as

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{[\varepsilon_{t-1}<0]} + \beta h_{t-1}. \tag{4.5}$$

4.1.2 Multivariate GARCH models

As it has been outlined in Chapter 2, multivariate GARCH models retain the ease of estimation of the univariate ones and together with their explicit parameterization are very popular with the academic community. Multivariate extensions allow the conditional variance-covariance matrix of the n-dimensional zero mean random variables depend on the information set, which is the σ-field generated by the past values of r_t. Letting the covariance matrix H_t be measurable with respect to $\Im_{t-1}$ and r_t be normally distributed asset returns, we can write

$$r_t \,|\, \Im_{t-1} \sim N(0, H_t). \tag{4.6}$$

Symmetric versions

The econometric approach behind the constant conditional correlation GARCH (CCC-GARCH) of Bollerslev (1990) is to decompose the covariance matrix H_t into the product of conditional standard deviations and correlations as follows:

$$H_t = D_t R D_t. \tag{4.7}$$

However, the assumption of constant conditional correlations appears to be far too restrictive and is not always supported by empirical evidence over long time periods. For this reason, Engle (2002) generalizes Bollerslev's (1990) model to allow for the dynamic evolution of the correlations, and by extension, more flexibility in the correlation process. One drawback is that they are restricted to the same dynamic structure regardless of the assets involved for all pairs of variables. In accordance with the hedging literature, this thesis implements the model in its benchmark form despite the (in)consistency issues and existence of bias in the estimated parameters as discussed in Aielli (2013)[1] and Caporin and McAleer (2014)[2] who make an attempt to improve the tractability of the model. Nonetheless, the correlations misspecifications and (ir)relevance of innovations do not appear to substantially impact the correlation dynamics since the estimators of the corrected and standard models perform very similarly and parameters yield almost identical values (such as Khalfaoui and Boutahar, 2012; Raza et al., 2019, or Sarwar et al., 2019).

In case of the DCC, the conditional covariance matrix H_t may be partitioned

1 He adopts the corrected DCC-GARCH (cDCC) that has desirable theoretical and empirical properties under reasonable regularity conditions and a modular stationarity principle. The correlation driving process Q_t, outlined later in this chapter, is reformulated due to the inconsistent empirical correlation matrix of standardized residuals $\bar{Q}$. The consistency is heuristically proven and restored in such a way that $Q_t = (1-\alpha-\beta)\bar{Q}+\alpha\epsilon^{*}_{t-1}\epsilon^{*T}_{t-1}+\beta Q_{t-1}$, where $\epsilon^{*}_{t-1} = \mathrm{diag}(\sqrt{Q_{t-1}})\epsilon_{t-1}$.

2 They state ten critical aspects of the DCC framework, among which the absence of mathematical and asymptotic properties, inconsistent estimator and the stated, rather than derived, representation of the model are reiterated.

as

$$H_t = D_t R_t D_t, \tag{4.8}$$

which is the modification against Equation 4.7 in that R_t is the $n \times n$ time-varying conditional correlation matrix with motion dynamics contrary to the constant specification. Formally, this matrix is symmetric positive definite such that

$$R_t = \begin{pmatrix} 1 & \rho_{12,t} & \dots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \dots & \rho_{2n,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1n,t} & \rho_{2n,t} & \dots & 1 \end{pmatrix}. \tag{4.9}$$

D_t is the $n \times n$ diagonal matrix of conditional time-varying standard deviations:

$$D_t = \begin{pmatrix} \sqrt{h_{1,t}} & 0 & \dots & 0 \\ 0 & \sqrt{h_{2,t}} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sqrt{h_{n,t}} \end{pmatrix}. \tag{4.10}$$

They are modelled by a set of univariate GARCH models with $\sqrt{h_{i,t}}$ being the i-th element on the diagonal. Therefore, the standard deviations in D_t can be obtained from Equation 4.2 which is adjusted for a multiple-series representation in the vector nested form as

$$h_{i,t} = \omega_i + \sum_{p=1}^{P_i} \alpha_{i,p} \varepsilon_{i,t-p}^2 + \sum_{o=1}^{O_i} \gamma_{i,o} \varepsilon_{i,t-o}^2 I_{[\varepsilon_{i,t-o}<0]} + \sum_{q=1}^{Q_i} \beta_{i,q} h_{i,t-q}, \tag{4.11}$$

for $i = 1, \dots, n$. The classical restrictions for the non-negativity of variance and stationarity conditions are imposed. It is noteworthy that the equation raised to the power of one represents a parameterization of the conditional variance. If we take a square root of it, then the standard deviation is parameterized. In such a case, we also have to take the absolute value of squared lagged terms.

For the off-diagonal elements of H_t this implies $[H_{ij,t}] = \sqrt{h_{i,t}}\sqrt{h_{j,t}}\rho_{ij,t}$ when $i \neq j$. The covariance matrix is positive definite for all t if and only if all the n conditional standard deviations are positive and non-zero and R_t is a positive definite matrix of full rank. These requirements need to hold in order to have sensible parameterization. For our purposes, if the covariance matrix H_t in Equation 4.8 is correctly identified, then the bivariate DCC-GARCH can be written as

$$H_t = \begin{pmatrix} h_{1,t} & \sqrt{h_{1,t}}\sqrt{h_{2,t}}\rho_{12,t} \\ \sqrt{h_{1,t}}\sqrt{h_{2,t}}\rho_{12,t} & h_{2,t} \end{pmatrix}. \tag{4.12}$$

In principle, the correlation matrix R_t is given by the following transformation:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{4.13}$$

where

$$Q_t^* = \begin{pmatrix} \sqrt{q_{11,t}} & 0 & \dots & 0 \\ 0 & \sqrt{q_{22,t}} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sqrt{q_{kk,t}} \end{pmatrix}. \tag{4.14}$$

The dynamic correlation structure takes the form of

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\bar{Q} + \sum_{m=1}^{M} a_m(\epsilon_{t-m}\epsilon_{t-m}^T) + \sum_{n=1}^{N} b_n Q_{t-n}, \tag{4.15}$$

where Q_t denotes the $n \times n$ symmetric positive definite covariance matrix conditional on the vector of standardized residuals while $\bar{Q} = \mathbb{E}\left[\epsilon_t\epsilon_t^T\right]$ is the $n \times n$ unconditional covariance matrix of the standardized residuals ϵ_t obtained by its sample counterpart $\frac{1}{T}\sum_{i=1}^{T} \epsilon_{t-i}\epsilon_{t-i}^T$. Parameters capture both the effects of past innovations and previous DCC on the current DCC. They satisfy the following restrictions: $a_m \geq 0$ for $m = 1, \dots, M$; $b_n \geq 0$ for $n = 1, \dots, N$; and $\sum_{m=1}^{M} a_m + \sum_{n=1}^{N} b_m < 1$. Therefore, it can be stated that for R_t to be positive definite, it suffices that Q_t is positive definite. As long as Q_t is positive definite, Q_t^* guarantees R_t.

The dynamic dependence of the correlations in equation Equation 4.15 can be simplified into the scalar form as follows:

$$Q_t = (1 - a - b)\bar{Q} + a(\epsilon_{t-1}\epsilon_{t-1}^T) + bQ_{t-1}. \tag{4.16}$$

Irrespective of the number of assets, there are only two parameters a and b that completely drive the time evolution of conditional correlations. The model is thus extremely parsimonious, which ensures the ease of estimation.

Finally, the correlation estimator can be expressed as

$$\begin{aligned}\rho_{ij,t} &= \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \\ &= \frac{(1-a-b)\bar{q}_{ij} + a\epsilon_{i,t-1}\epsilon_{j,t-1}^{T} + bq_{ij,t-1}}{\left[(1-a-b)\bar{q}_{ii} + a\epsilon_{i,t-1}^{2} + bq_{ii,t-1}\right]\left[(1-a-b)\bar{q}_{jj} + a\epsilon_{j,t-1}^{2} + bq_{jj,t-1}\right]},\end{aligned} \tag{4.17}$$

where q_t are the elements of matrix Q_t and correlation estimators ρ_t are the elements of matrix R_t.

Estimation

Parameter estimation is carried out by maximizing the log-likelihood function for the model. This is possible due to the assumption of normality in Equation 4.6. Information embedded both in the volatility processes and correlation dynamics are estimated independently, the latter is updated as new information is received. The variance parameters serve us as nuisance parameters, the correlation parameters are the parameters of interest. We follow the two-step method of Engle (2002) and Engle and Sheppard (2001). First, assuming no cross effects, the individual volatility processes are estimated one at a time by fitting an appropriate univariate GARCH model to each asset return series. Subsequently, the correlation processes are estimated from the vectors of standardized residuals obtained in the first step as follows $\epsilon_{i,t} = r_{i,t} \,/\sqrt{h_{i,t}}$.[3] The conditional distribution of the standardized returns can be either multivariate standard normal or multivariate (skew) Student's-t. We confine ourselves to the former one.

The log-likelihood is expressed as follows:

$$\begin{aligned}L &= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|H_t| + r_t^T H_t^{-1} r_t) \\ &= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t R_t D_t| + r_t^T D_t^{-1} R_t^{-1} D_t^{-1} r_t) \\ &= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \epsilon_t^T R_t^{-1}\epsilon_t) \\ &= -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + r_t^T D_t^{-1} D_t^{-1} r_t - \epsilon_t^T\epsilon_t + \log|R_t| + \epsilon_t^T R_t^{-1}\epsilon_t).\end{aligned} \tag{4.18}$$

3 $r_{i,t}$ is either mean zero return or the residuals from an ARMA-filtered time series.

Under the assumption of normality, the last equation in Equation 4.18 can be written as the sum of a volatility part and a correlation part. Letting θ denote the parameters of the univariate GARCH model in D_t and ϕ denote the additional parameters in R_t:

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi). \tag{4.19}$$

The volatility component is given as

$$L_V(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t|^2 + r_t^T D_t^{-2} r_t) \tag{4.20}$$

and could be rewritten as the sum of individual GARCH log-likelihoods:

$$L_V(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{n}\left(\log(2\pi) + \log(h_{i,t}) + \frac{r_{i,t}^2}{h_{i,t}}\right). \tag{4.21}$$

The first step is to maximize the log-likelihood and find the value of

$$\hat{\theta} = \arg\max\{L_V(\theta)\}, \tag{4.22}$$

which can be jointly maximized by separately maximizing each n term in Equation 4.21.

The correlation term has the following form:

$$L_C(\theta, \phi) = -\frac{1}{2}\sum_{t=1}^{T}(\log|R_t| + \epsilon_t^T R_t^{-1}\epsilon_t - \epsilon_t^T\epsilon_t) \tag{4.23}$$

and can be maximized with respect to ϕ as $\hat{\theta}$, the value obtained in the first step, is taken as given.

Formally, the maximization problem can be reduced to

$$\max_{\phi}\{L_C(\hat{\theta}, \phi)\}. \tag{4.24}$$

Asymmetric version

The assumption of conditional correlations obeying the same dynamics, and hence evolving in an identical manner, may be inadequate in some practical applications. On that account, Cappiello et al. (2006) propose a model capable of allowing for the asymmetric behavior in conditional asset returns volatilities and correlations, on top of the series-specific news impact and smoothing parameters. The model can better capture heterogeneity present in our data. For that reason, reproducing the multivariate model for the asymmetric responses to positive versus negative returns, we extend our analysis by the asymmetric DCC-GARCH (ADCC-GARCH). The elements of D_t from Equation 4.10 follow the univariate GJR-GARCH(1,1) process. The evolution of correlations in Equation 4.15 can thus be modified as follows:

$$\begin{aligned} Q_t = \Big(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\Big)\bar{Q} - \sum_{k=1}^{K} g_k \bar{N} + \sum_{m=1}^{M} a_m(\epsilon_{t-m}\epsilon_{t-m}^T) + \\ + \sum_{k=1}^{K} g_k(n_{t-k}n_{t-k}^T) + \sum_{n=1}^{N} b_n Q_{t-n}, \end{aligned} \tag{4.25}$$

where a, b, and the asymmetric term g are $n \times n$ parameter matrices. This thesis uses the scalar version of the Generalized ADCC-GARCH as the parameter matrices are herein replaced by their scalar representation. As the expectation of $\bar{Q}$, $\mathbb{E}\left[\epsilon_t\epsilon_t^T\right]$, is infeasible, it is replaced by its sample counterpart $T^{-1}\sum_{t=1}^{T}\epsilon_t\epsilon_t^T$. In the same way, $\bar{N}$ is equal to $\mathbb{E}\left[n_t, n_t^T\right]$ which can be estimated by its sample analogue $T^{-1}\sum_{i=1}^{T} n_t n_t^T$. $n_t = I_{[\epsilon_t<0]} \odot \epsilon_t$, with $I[\bullet]$ being a $k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise. $\odot$ refers to the Hadamard product, i.e. element-by-element multiplication. For Q_t to be positive definite for all realizations, necessary and sufficient conditions are $a_m \geq 0$ for $m = 1, \ldots, M$; $b_n \geq 0$ for $n = 1, \ldots, N$; $g_k \geq 0$ for $k = 1, \ldots, K$, and $\sum_{m=1}^{M} a_m + \sum_{n=1}^{N} b_n + \delta\sum_{k=1}^{K} g_k < 1$, where δ is the maximum eigenvalue $\left[\frac{1}{\sqrt{\bar{Q}}}\bar{N}\frac{1}{\sqrt{\bar{Q}}}\right]$. This constraint can be easily imposed, and thus makes the estimation of the scalar ADCC analogous to that of the scalar DCC.

4.2 Hedging and hedging performance measures

Perfect hedge means that the change in basis (or base) is zero. The formula for basis (Fama and French, 1987) reads as

$$B = S - F, \tag{4.26}$$

where S denotes the hedged asset's spot price and F is the price of the underlying futures contract.[4] This strategy is a purely theoretical concept in the

4 For notational purposes, capital letters represent prices and small letters designate asset returns.

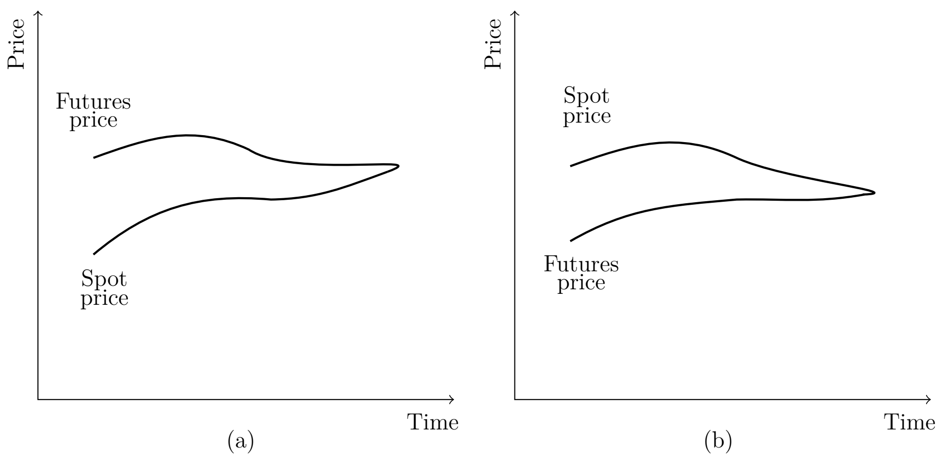
commodity markets since it is infeasible under normal conditions to (cross) hedge 100% of the respective asset due to the circumstances mentioned below.

It is worth noting that the majority of the studies on financial time series literature ascertain that any type of hedge is more effective than a naked exposure. The simplest hedging rule is realized through the naïve hedge strategy. It represents minimizing the exposure in that the investor who is long in the spot should sell the unit of futures contracts and buy them back when he sells the spot. If the prices between these two markets change by the same amount, the investor's net position remains unchanged, resulting in a perfect hedge (Myers, 1991).

Basis risk arises due to imperfect and complex hedges. Hull (2014) states several reasons why this is such a case. The asset whose price is to be hedged is different to the asset underlying the futures contract. The investor might not be sure of the exact date the asset will be bought or sold. In addition, the futures contract may be required to be closed out before its delivery month, which happens almost always given the fact that financial contracts mature every three months. On the other hand, commodity contracts are available each month. Market expectations and the cost of carry are equally important to bear in mind. For these reasons, a perfect hedge is rare.

Owing to the convergence of the futures price to the spot price, one can expect basis risk to be zero at the time of the futures contract's expiration. Prior to expiration, basis can take positive or negative values. The former occurs when the spot price increases more than the futures price and is referred to as *normal backwardation*. The opposite applies for *contango*, i.e. weakening of the basis.

Figure 4.1: Variation of basis as the delivery month is approached



Source: Author based on Hull (2014).

4.2.1 Optimal hedge ratio

The first methodological part of this thesis, that is the estimation of conditional variance-covariance matrix, provides us with the inputs for the optimal hedge ratio (OHR). It goes without saying that these by-products of correlation estimation can have different specifications. By extension, this analysis will also allow us to identify the effective optimal portfolio design and optimal cross hedging instrument on top of the possible solution to the IMO 2020 quandary.

Johnson (1960) defines MVHR as the ratio of the covariance between the underlying spot and futures returns to the variance of portfolio returns on the given information set. Historically, it is known as the hedging rule. In order to minimize the portfolio risk, the estimation of the return of a hedged portfolio is performed. Let r_t^H be the revenue of a certain hedging position at time t, that is the return on holding the portfolio, then we can write

$$r_t^H = s_t - \lambda_t f_t, \tag{4.27}$$

where λ_t is the risk-minimizing hedge ratio representing the number of futures contracts that the hedger must sell for each unit of the spot asset. s_t denotes the return of the spot position on which price risk is borne and f_t is the return of the futures position. To emphasize the point, in order to minimize the risk, and thereby reduce its cost, a long position taken in one asset should be hedged with a second asset's short position. This is to ensure that losses incurred in one market, either spot or futures, are offset with gains from the other market. As a result, the OHR can be seen as the proportion of the short (long) spot position that is covered by futures sales (purchases) (Cifarelli, 2011).

The conditional variance in Equation 4.27 is given as

$$\mathrm{var}(r_t^H \mid \Omega_{t-1}) = \mathrm{var}(s_t \mid \Omega_{t-1}) + \lambda_t^2 \mathrm{var}(f_t \mid \Omega_{t-1}) - 2\lambda_t \mathrm{cov}(s_t, f_t \mid \Omega_{t-1}). \tag{4.28}$$

Johnson (1960) demonstrates that the OHR is equal to the value of r_t^H minimizing the conditional variance of the hedged portfolio returns on the given information set:

$$\lambda_t^* = \arg\min_{\lambda_t} \mathrm{var}(r_t^H \mid \Omega_{t-1}). \tag{4.29}$$

To derive the OHR at time t conditional on the information available at $t-1$, it is necessary to take the partial derivative of Equation 4.28 with respect to λ_t, set it equal to zero and solve for λ_t. It is worth noting that if futures returns are martingale processes and spot and futures returns are jointly normal, the optimal hedge ratio from whatever hedging strategy converge to the MVHR (Cifarelli and Paladino, 2015).

Within the context of the estimated parameters from the MGARCH models, Baillie and Myers (1991) and Kroner and Sultan (1993) note that the optimal time-varying conditional hedge ratio can be written as

$$\lambda^*_{t|\Omega_{t-1}} = \frac{\operatorname{cov}(s_t, f_t \mid \Omega_{t-1})}{\operatorname{var}(f_t \mid \Omega_{t-1})}, \tag{4.30}$$

where Ω_{t-1} is the information set available at time $t-1$. $\operatorname{Cov}(s_t, f_t \mid \Omega_{t-1})$ denotes the conditional covariance between spot and futures returns and $\operatorname{var}(f_t \mid \Omega_{t-1})$ is the conditional variance of futures returns. This specification is identical to the commonly designated spot-futures relationship as long as it remains constant.

To complement our analysis with a more conventional approach, we use the standard econometric practice for cross hedging, the ordinary least squares (OLS) method. In the simplest case, the static or unconditional hedge ratio is based on the model proposed by Ederington (1979). A linear relationship between returns is given as follows:

$$s_t = \mu + \lambda f_t + u_t, \quad u_t \overset{iid}{\sim} N(0, \sigma^2), \tag{4.31}$$

where μ and λ are the regression parameters; s_t and f_t denote the time t spot and futures returns, respectively, and u_t is the random error term. The OLS estimate of the coefficient on f_t is the time t optimal static hedge ratio estimator λ^*_t.

Furthermore, the traditional hedge ratio is nested within the conditional hedge ratio. In other words, the slope coefficient of the OLS regression represents the unconditional covariance between spot and futures returns and may be taken as given in the following equation:

$$\lambda^*_t = \frac{\operatorname{cov}(s_t, f_t)}{\operatorname{var}(f_t)}. \tag{4.32}$$

The difference between Equation 4.32 and Equation 4.30 is the conditionality with respect to what is known at time $t-1$. The former does not take into account the arrival of new information because the joint distribution of spot and futures returns remains the same over time. As it is discussed in Chapter 2, this is rarely a case due to the stochastic nature of returns. In the latter equation, conditional second-order moments have emerged; accordingly, the hedge ratio is set every period and is dynamic.

4.2.2 Hedging effectiveness index

One of the most widely used criteria for evaluating hedging effect for different models is the hedging effectiveness index (HEI) derived by Ederington (1979). The measure of relative performance improvements is represented by the percentage variance reduction given as

$$HEI = 1 - \frac{\mathrm{var}(r_t^H)}{\mathrm{var}(r_t^U)}, \tag{4.33}$$

where $\mathrm{var}(r_t^H)$ denotes the smallest variance of the returns to a hedged portfolio and $\mathrm{var}(r_t^U)$ is the variance of the returns to an unhedged portfolio established on the spot market. They can be expressed respectively as

$$\mathrm{var}(r_t^U) = \mathrm{var}(s_t), \tag{4.34}$$

$$\mathrm{var}(r_t^H) = \mathrm{var}(s_t) + \lambda^2 \mathrm{var}(f_t) - 2\lambda \mathrm{cov}(s_t, f_t). \tag{4.35}$$

As a matter of course, Equation 4.33 also holds for the conditional case:

$$\mathrm{var}(r_t^U) = \mathrm{var}(s_t \mid \Omega_{t-1}), \tag{4.36}$$

$$\mathrm{var}(r_t^H) = \mathrm{var}(s_t \mid \Omega_{t-1}) + \lambda_{t-1}^2 \mathrm{var}(f_t \mid \Omega_{t-1}) - 2\lambda_{t-1} \mathrm{cov}(s_t, f_t \mid \Omega_{t-1}). \tag{4.37}$$

The index evaluates the extent to which changes in the fair value of the futures contract returns offset changes in the fair value of the spot returns. Subtracting it from one yields the percentage variance reduction size derived from a hedged portfolio over an unhedged portfolio. As might be expected, higher positive values of the HEI indicate a better hedging approach established on the corresponding method, leading to a larger risk reduction, and can thus be regarded as a superior hedging strategy.

Chapter 5

Data description and preliminary analysis

This chapter attempts to briefly describe the data and their preparation. Care has been taken to ensure that the subsequent analysis is carried out readily without any practical issues. Our empirical analysis is based on spot and futures returns of energy commodities and a convincing rationale for their particular selection is given below. New low-sulphur fuel oil futures listed on the Chicago Mercantile Exchange (CME) and the Intercontinental Exchange (ICE) cannot be evaluated because the first batch of these derivative contracts was launched in December 2018 and February 2019, respectively. Dynamic conditional correlations models require a sufficient time-frame, thereby allowing us to infer particular features of our time series accordingly. For this reason, we have recourse to cross hedging.

The data were obtained from three separate sources. The New York Mercantile Exchange (NYMEX) futures contracts were extracted from the U.S. Energy Information Administration (EIA)[1], while the European complements were collected from the ICE Market data[2] under the auspice of the Intercontinental Exchange. Spot prices were retrieved from the selected ports as shown on the website of Bix Bunker Index[3]. Our data set consists of the time series of daily closing prices. The sample period runs from April 2, 2008, until March 30, 2020, yielding a total of 3074 daily observations. What needs to be accentuated is that our intention was not to define the time span from the global financial crisis (GFC) through the coronavirus disease 2019 (COVID-19) pandemic, but

1 `https://www.eia.gov/dnav/pet/pet_pri_fut_s1_d.htm`; EIA (2020).
2 `https://www.theice.com/market-data`; ICE (2020a).
3 `https://bunkerindex.com/index.php`; BIX (2020).

given how much history is available for the spot prices, we made this decision. It may give us some interesting findings particularly with regard to the former extreme economic disruption.

We organize the rest of this chapter as follows. Besides the introduction of selected commodities in Section 5.1, their graphical representation is examined since any econometric analysis necessitates visual inspection of data. The subsection is divided into spot and derivatives markets to ascertain the difference in patterns of the individual financial instruments. Section 5.2 establishes several filtering rules so that the estimation would not be susceptible to estimation biases. In Section 5.3, we provide descriptive statistics to report the basic features of our data and recognize some stylized facts. In the end, we comment on the stationarity within our data set to draw appropriate conclusions in the chapter to follow.

5.1 Selected commodities

5.1.1 Futures contracts

Table 5.1: Description of futures contracts

	Venue	Units	Quote	Tick	Delivery	Observations
WTI	NYMEX	1000 barrels	US$	0.01	Cushing, Oklahoma	3024
ULSD	NYMEX	42000 gallons	US$	0.01	New York, New York	3009
RBOB	NYMEX	42000 gallons	US$	0.01	New York, New York	3011
Brent	ICE	1000 Barrels	US$	0.01	Sullom, Scotland	3071
Gasoil	ICE	100 metric tons	US$	0.25	Amsterdam, Rotterdam, Antwerp	3070

Note: ULSD and RBOB tick values are scaled by 10^2.
Source: `https://www.cmegroup.com/`; CME (2020), & `https://www.theice.com/index`; ICE (2020b).

Above, we present the five most actively traded futures contracts in the world.

It should be pointed out that prices of futures contracts specify the earliest delivery date.

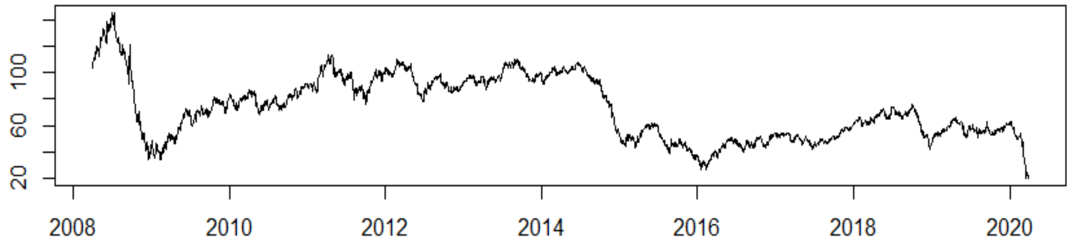
Regardless of the specifications, crude oil may be held in refiners' inventory as it does not need to be processed into a final product immediately. Having a powerful exploratory potential, it is also a complementary product to other commodities as well as their substitute. West Texas Intermediate Crude Oil (WTI) is used as a global benchmark in oil pricing. Each futures contract expires on the third business day before the 25th calendar day of the month preceding the delivery month. No. 2 heating oil is traded as New York Harbor ultra-low sulphur No. 2 diesel (ULSD hereafter). Furthermore, there was a change in the grade of gasoline at NYMEX in 2006. Each Reformulated Blendstock for Oxygenate Blending Gasoline (RBOB) contract expires on the last business day of the month preceding the delivery month just as ULSD.

North Sea Brent is the European crude oil counterpart to WTI. Despite being a light crude oil, Brent is not preferred as it contains 0.37% of sulphur against 0.24% (Chang et al., 2006). For that reason, Brent is cheaper than WTI which has also higher liquidity given its volume and open interest. Each contract expires on the last business day of the second month preceding the relevant delivery month. Prices for IMO 2020 compliant fuels are also based on the price of gasoil, and hence it must be used in our empirical analysis. It is the ICE's benchmark in low sulphur futures and the leading global product standard aside from crude oils. Its open interest is more than twice the combined open interest in both of ULSD and RBOB. Finally, each futures contract expires two business days prior to the 14th calendar day of the delivery month.

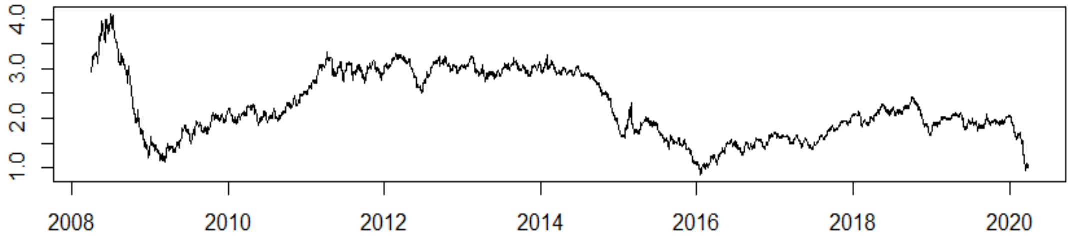
Next, we plot the data. The corresponding returns are in Figure A.2 in the Appendix. Prices of petroleum-refined products mimic WTI and Brent in a particular way, being relatively stable only in few cases with a certain pattern of a gradual increase shortly after 2016. It appears that the prices hit their bottom in the spring of 2020 due to the coronavirus pandemic, falling even lower than during the aftermath of the GFC. RBOB has suffered its biggest price drop contrasting other energy commodities. It may be attributed to a flat or declining gasoline consumption contingent on its relatively high inventories. On the other hand, ULSD and gasoil did not witness such a severe plunge as a result of increased consumption and lower inventories. The most volatile commodity seems to be ULSD as it is priced off of crude oil and can be utilized in a greater variety of fields contrary to other refined products. As one could expect, all returns show the major volatility clusters happening around the same time, and that is 2009, 2015-2016 and very likely 2020.

Figure 5.1: Prices of futures contracts over time

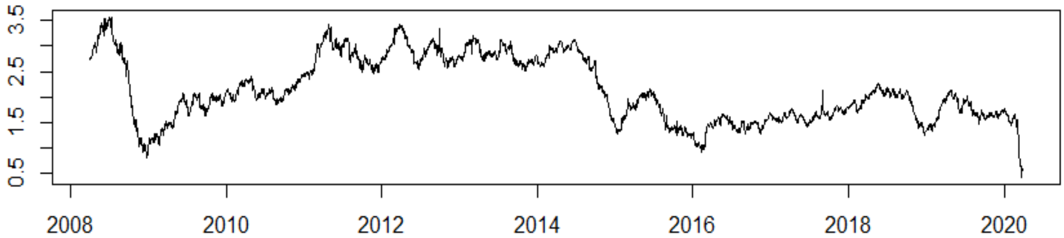
(a) WTI



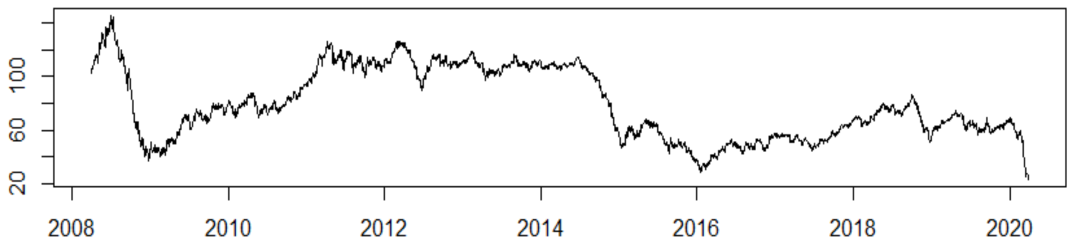
(b) ULSD



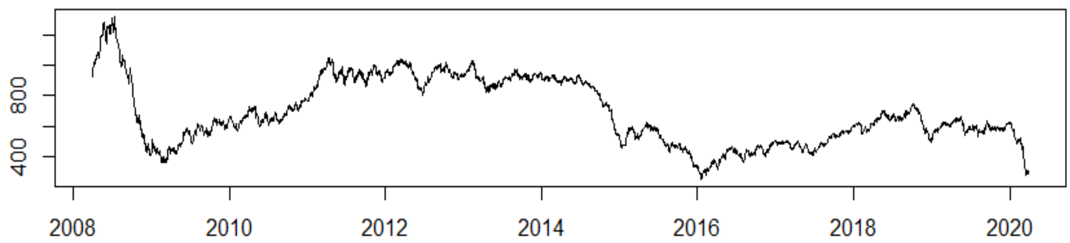
(c) RBOB



(d) Brent



(e) Gasoil



Source: Author's computations.

5.1.2 Spot contracts

There are four key bunkering ports which together cover about 25% of global bunker volumes (Ship & Bunker, 2020). The percentage may be higher given the price setting decisions in neighbouring ports. Marine bunkers take up 7% of the crude oil barrel (Halff et al., 2019), and are thus significantly affected by oil price fluctuations. Intermediate fuel oil 380 (IFO 380) has been selected as a paradigm of the first scenario because it is the most widely used high-sulphur fuel. The grade '380' centistokes refers to a maximum viscosity. We could have chosen IFO 180; however, we were not able to obtain the data in every port. Marine gasoil (MGO) is then a very typical example of the second scenario. It is a 100% distillate oil akin to diesel with 0.1% up to 1.5% of sulphur (ICCT, 2007). We work with the lower sulphur alternative.

Table 5.2: Description of spot contracts

Symbol	Delivery Location	Observations
RIFO	Rotterdam	3074
RMGO	Rotterdam	3074
SIFO	Singapore	3074
SMGO	Singapore	3074
FIFO	Fujairah	3074
FMGO	Fujairah	3074
HIFO	Houston	3068
HMGO	Houston	3068

Note: Prices used for the analysis are quoted in the U.S. dollar per metric tonne and are quoted as delivered. The first letters of abbreviations indicate a port.
Source: `https://bunkerindex.com/index.php`; BIX (2020).

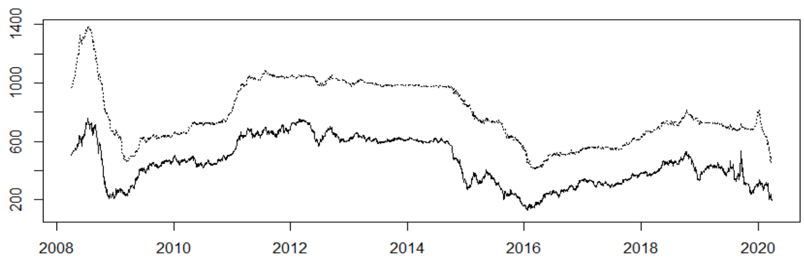
Now, let us briefly comment on the time series of the spot contracts in Figure 5.2. The return series are shown in Figure A.1 in the Appendix. For ease of exposition, prices are reported in the form of a differential between MGO and IFO. What is prominent is the extreme price fluctuation of bunker fuel oils irrespective of the sulphur content when compared to the futures contracts. The prices follow a similar pattern across the globe. We can observe the increased bunker prices experienced between 2010 and 2012, a more pronounced bunker fluctuation of 2014 to 2017 due to the drastic drop in global oil prices attributable to the excess supply of oil brought about by the shale revolution.

Figure 5.2: Spot prices differential according to ports

(a) Rotterdam

(b) Singapore

(c) Fujairah



(d) Houston

Note: Solid lines represent IFOs, dotted lines designate MGOs.
Source: Author's computations.

There was also a drop in value of either of the two assets during the GFC and the 2014-2015 commodities price crash. Prior to the rollout of IMO 2020, prices noticeably increased particularly with regard to MGO. Nevertheless, the trend was halted by the spread of the coronavirus with the series reaching the lowest point ever.

5.2 Data construction

For the subsequent empirical analysis, we adjust our sample to obtain inputs that have more attractive statistical properties than market prices. Return series are computed as the changes in the continuously compounded natural logarithms of closing prices at time t and $t-1$. Formally, it can be written as $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, where $r_{i,t}$ represents the log-returns of the price series of commodity i at time t. $P_{i,t}$ denotes the price of commodity i at time t and $P_{i,t-1}$ is the corresponding lagged price.

At first, there are specific days when trading activity is naturally low or the market is closed, which may cause estimation bias. For that reason, we remove all observations that fall on weekends, U.S. federal holidays and some state holidays[4] according to the trading schedule of each exchange. In addition, provided that some values are missing in the respective time series due to different exchanges and ports' operation, they are replaced by the preceding day's values as there are only few such cases.

Having generated the return series, it is also critical to further adjust the data set when we consider pairs of time series for the correlation analysis. As we have already removed zero value returns, the pairwise correlations have to be synchronized at each point in time, which clearly leads to a reduction in the number of observations.

5.3 Descriptive statistics

In this subsection, we review some key facts regarding the adjusted data set. Descriptive statistics are fairly similar to each other for all return series with the exception of RBOB. In this spirit, the central location for the data appears to be a negative close to zero value. There are only negligible differences in other values. Considering standard deviation, the data points are found to be

4 Martin Luther King Jr. Day, President's Day, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, Christmas Day, and New Year's Day.

Table 5.3: Descriptive statistics of daily returns

	Mean	Max	Min	St. Dev.	Skewness	Kurtosis
WTI	-0.05	21.36	-28.22	2.58	-0.59	17.16
ULSD	-0.04	10.41	-19.75	2.06	-0.54	10.04
RBOB	-0.05	21.66	-38.42	2.71	-1.49	27.64
Brent	-0.05	13.64	-27.58	2.29	-0.61	13.79
Gasoil	-0.04	12.09	-14.00	1.89	-1.42	8.04
RIFO	-0.04	18.10	-25.05	2.39	-0.45	13.86
RMGO	-0.04	10.35	-20.72	2.29	-0.26	10.01
SIFO	-0.03	15.58	-27.56	2.29	-0.66	14.92
SMGO	-0.04	11.06	-20.76	1.72	-0.66	13.42
FIFO	-0.03	14.02	-27.63	2.32	-0.68	15.23
FMGO	-0.02	10.05	-9.93	1.03	-0.71	17.31
HIFO	-0.03	20.39	-25.39	2.45	-0.03	13.06
HMGO	-0.03	8.89	-10.22	1.75	-0.14	7.33

Note: Values for mean, maximum, minimum and standard deviation are displayed in %.
Source: Author's computations.

spread out over a wider range of values. The highest standard deviation is reported for RBOB, whereas FMGO exhibits the lowest variability in terms of dispersion.

Examining frequency distribution, negative skewness indicates that the mass of the distribution is concentrated on the right side and the tail is longer or fatter on the left side for all analyzed commodities. Kurtosis describes the shape of a distribution. In a similar way, it further underpins the reasoning for departure from normality in our data. Return series are leptokurtic, meaning they have long and heavy tails and a tall and sharp peak. Higher kurtosis signals that there are more infrequent extreme deviations in our data. Again, RBOB reached the lowest and highest value for skewness and kurtosis, respectively. It might signify that its distribution has the most outliers out of all selected commodities, which could also be observed by visual inspection in the preceding subsection. Based on the above reasoning, we can conclude that the energy returns display characteristic features common to financial time series.

5.4 Selected test statistics

To conclude, we summarize the data in Table 5.4 using common diagnostic tests to check the adequacy of the return series for the subsequent application. The results warrant some discussion.

First, the classical Jarque-Bera (JB) test (Jarque and Bera, 1987) is applied to detect whether errors are normally distributed. JB statistic displays that the skewness and kurtosis of our time series do not match normal distribution as the joint null hypothesis is strongly rejected. Next, we report the Ljung-Box Q-statistics (Ljung, 1978) for up to 1st and 10th orders. It tests the existence of serial autocorrelation in the respective time series. The null hypothesis is rejected at the specified conventional levels implying that at least one autocorrelation is not zero in all return series. The Q-statistic for squared returns also indicate that the group of autocorrelations is significantly different from zero at the 1% significance level. These values strongly suggest the presence of conditional heteroskedasticity. Further, the Lagrange multiplier (LM) test of Engle (1982) for ARCH disturbances tests the null hypothesis of no ARCH effects. The test statistic converges to χ^2 distribution with q degrees of freedom. It indicates that there exists conditional heteroskedasticity so we reject the null hypothesis in favour of the alternative up to 1st and 10th orders. This fact points to the use of (M)GARCH models for estimating dynamic conditional correlations given how variance changes through the passage of time.

In order to test the stationarity of the respective return series, it is necessary to perform unit root testing. Dickey and Fuller (1979) formally developed such a procedure. Due to the lagged changes incorporated in the models, the augmented Dickey-Fuller test will be employed. Alternatively, the Phillips-Perron's (1988) test may be used, allowing for the presence of a structural break whose exact date is assumed to be known. Nonetheless, as Enders (2014) puts it, both these tests are biased towards not rejecting the null hypothesis even though the series is, in fact, stationary. Their power[5] declines when a time series has a characteristic root near unity in absolute value; and as a matter of fact, it cannot properly distinguish a true unit root process. The results for the ADF test are included in Table 5.4. The associated values indicate that we can reject the null hypothesis that the series are integrated of order one at any conventional significance level. Instead, we can compare the t-statistic with the

5 In other words, the probability of rejecting a false null hypothesis. A test with good power will thus correctly reject the null hypothesis.

critical values in Table A.1 in the Appendix. Since they are greater than the t-statistic, we can reject the null hypothesis. Therefore, our objects of interest can be adequately approximated by long time averages based on the single set of realizations.

As another option, the stationarity tests were devised. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) is the most widely used one of this type. It circumvents the aforementioned issue by directly testing the null hypothesis of stationarity against the alternative of the unit root's presence. While the data are estimated under the alternative hypothesis for the ADF test, the stationarity test assumes estimation under the null hypothesis. As noted, the values obtained from the KPSS test maintain the hypothesis that the individual return series are stationary. It is also possible to directly compare the statistic with the critical values in Table A.1 in the Appendix. Since it is less than the critical values, we fail to reject the null hypothesis at the 10% significance level. Likewise the ADF test, we thus conclude that the return series are stationary.

Table 5.4: Selected test statistics for daily returns

	JB	$Q(1)$	$Q(10)$	$Q^2(1)$	$Q^2(10)$	ARCH(1)	ARCH(10)	ADF	KPSS
WTI	25455***	18.71***	35.93***	370.13***	1469.73***	367.92***	784.83***	-11.75***	0.1777
ULSD	6359.4***	7.78***	25.55***	105.63***	234.93***	103.58***	234.93***	-13.34***	0.1232
RBOB	77289***	1.61*	17.12**	51.41***	1001.99***	53.348***	728.7***	-12.43***	0.1727
Brent	15091***	11.99***	49.64***	150.43***	874.33***	150.88***	442.35***	-11.53***	0.2201
Gasoil	3252.7***	5.97**	21.02**	117.74***	873.45***	116.47***	369.50***	-12.73***	0.1428
RIFO	15201***	24.99***	67.62***	123.70***	989.99***	124.90***	398.65***	-11.94***	0.1508
RMGO	6324.5***	4.14**	25.20***	52.13***	548.78***	51.87***	305.08***	-13.15***	0.1229
SIFO	18428***	5.85**	41.21***	148.69***	975.69***	149.15***	431.74***	-11.96***	0.1503
SMGO	14127***	4.90**	91.21***	73.02***	639.71***	73.50***	392.17***	-12.26***	0.1522
FIFO	19402***	2.63*	34.50***	72.35***	790.54***	72.69***	404.6***	-12.00***	0.1317
FMGO	26471***	47.27***	134.50***	95.59***	394.62***	96.56***	246.69***	-9.05***	0.2482
HIFO	12937***	2.21*	45.22***	112.27***	676.03***	111.64***	305.97***	-11.96***	0.1301
HMGO	2410.5***	57.18***	91.76***	117.37***	712.28***	116.67***	312.86***	-12.30***	0.1703

Note : JB stands for the Jarque-Bera test.Q(I) and Q^2(I) stand for the Ljung-Box test of the return and squared return series for up to the Ith order of serial (auto)correlation, respectively. ARCH(I) test denotes the ARCH-LM test of heteroskedasticity statistics of order I. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'. The ADF and KPSS tests are conducted with automated lag selection. For the former, the optimal lag length is determined based on the Bayesian information criterion (BIC).
Source: Author's computations.

Chapter 6

Empirical analysis and discussion of results

This chapter formally presents the empirical results with correlations as a starting point that are extracted by means of both symmetric and asymmetric models. Not accounting for cargo-handling and voyage costs, we investigate the hedging effectiveness of the energy commodities. Furthermore, we address differences across regional markets, stating certain limitations in our econometric framework. In the process of such measurement, different performances are utilized. We then draw a comparison between our results and the existing literature with the ensuing concluding discourse that could be regarded as the main value added of our thesis. The sample spans the period between 2008 and 2020, which provides us with sufficient observations without compromising on the accuracy of our estimates. The time-frame is rich enough to show the reaction of prices and returns to news announcements and immediate response to new information. Econometric estimation along with additional computations are performed in the free and open source software RStudio.

The rest of this chapter is laid out as follows. Having fitted the appropriate models, we describe how the correlations between pairs of commodities evolve in time in Section 6.1. Section 6.2 examines hedging devices for a shipping industry based on the symmetric or asymmetric responses to the fluctuations of the selected commodities. Section 6.3 attempts to detect the best possible model for the bunker energy sector as we further make use of a moving window scheme. This is to identify an effective hedging instrument and a reasonable hedging strategy that would hold in the future. Addressing all four hypotheses, concluding remarks are summarized in the last two sections with the discussion of the overall performance of the models.

6.1 Quantifying the dynamics of correlations

This subsection studies the dynamic evolution of financial correlations between pairs of commodities. Before we report the findings of the conditional correlations, let us shortly describe the unconditional equivalents to fully appreciate the former approach.

6.1.1 Unconditional correlations

The degree of a linear relationship between two variables, in our case series, may be given in the form of the Pearson product-moment correlation coefficient (PPMCC) as follows:

$$\rho_{fs} = \frac{\mathrm{cov}(f, s)}{\mathrm{var}(s)\mathrm{var}(f)} = \frac{\mathbb{E}\left[(f - \bar{f})(s - \bar{s})\right]}{\mathrm{var}(s)\mathrm{var}(f)}, \tag{6.1}$$

where f and s define futures and spot returns, and $\bar{f}$ and $\bar{s}$ denote their means, respectively. The closer in absolute value to 1, the stronger the linear relationship is.

Tables 6.1 and 6.2 give the unconditional correlations between bunker returns and futures returns. In the cases of Rotterdam and Singapore, the LSFO alternatives appear to be more correlated with the futures contracts than their heavy fuel counterparts. The reverse is true for Fujairah and Houston. The highest correlations could be observed for gasoil and practically any spot contracts with the highest correlations reaching as high as 50% for the interconnection with RMGO. Other futures contracts tend to share a very similar nexus in the respective port which may be attributed to disregarding temporal variation in our data.

On that account, it worth mentioning that working with fixed correlations is not ideal. The term *linear* itself suggests that there are certain limitations of the coefficient as it is usually distorted in favour of any errors in observations. Financial correlations are indeed evolving in time, which is precisely what the PPMMCC fails to capture, and by contrast, the conditional correlations models document. For that reason, one should be careful to avoid solid and set-in-stone interpretations following from the unconditional correlations analysis. Therefore, we now turn to a more complex analysis.

Table 6.1: Unconditional correlations – Rotterdam, Singapore

Panel A	RIFO	WTI	ULSD	RBOB	Brent	Gasoil
RIFO	1					
WTI	**0.2571**	1				
ULSD	**0.2489**	0.8063	1			
RBOB	**0.2155**	0.6642	0.7029	1		
Brent	**0.2825**	0.8767	0.8756	0.7212	1	
Gasoil	**0.3928**	0.5935	0.6705	0.5004	0.6628	1

Panel C	SIFO	WTI	ULSD	RBOB	Brent	Gasoil
SIFO	1					
WTI	**0.1559**	1				
ULSD	**0.1681**	0.8063	1			
RBOB	**0.1459**	0.6642	0.7029	1		
Brent	**0.1459**	0.8767	0.8756	0.7212	1	
Gasoil	**0.2772**	0.5935	0.6705	0.5004	0.6628	1

Panel B	RMGO	WTI	ULSD	RBOB	Brent	Gasoil
RMGO	1					
WTI	0.**2448**	1				
ULSD	**0.2816**	0.8063	1			
RBOB	**0.2143**	0.6642	0.7029	1		
Brent	**0.2830**	0.8767	0.8756	0.7212	1	
Gasoil	**0.5024**	0.5935	0.6705	0.5004	0.6628	1

Panel D	SMGO	WTI	ULSD	RBOB	Brent	Gasoil
SMGO	1					
WTI	**0.1580**	1				
ULSD	**0.1772**	0.8063	1			
RBOB	**0.1772**	0.6642	0.7029	1		
Brent	**0.1863**	0.8767	0.8756	0.7212	1	
Gasoil	**0.3193**	0.5935	0.6705	0.5004	0.6628	1

Note : Each panel displays unconditional correlations between a bunker return and five futures returns. Values of interest are reported in bold.

Source: Author's computations.

Table 6.2: Unconditional correlations – Fujairah, Houston

Panel A	FIFO	WTI	ULSD	RBOB	Brent	Gasoil
FIFO	1					
WTI	**0.1454**	1				
ULSD	**0.1627**	0.8063	1			
RBOB	**0.1653**	0.6642	0.7029	1		
Brent	**0.1755**	0.8767	0.8756	0.7212	1	
Gasoil	**0.2411**	0.5935	0.6705	0.5004	0.6628	1

Panel C	HIFO	WTI	ULSD	RBOB	Brent	Gasoil
HIFO	1					
WTI	**0.2127**	1				
ULSD	**0.2092**	0.8063	1			
RBOB	**0.1840**	0.6642	0.7029	1		
Brent	**0.2449**	0.8767	0.8756	0.7212	1	
Gasoil	**0.2783**	0.5935	0.6705	0.5004	0.6628	1

Panel B	FMGO	WTI	ULSD	RBOB	Brent	Gasoil
RMGO	1					
WTI	**0.0931**	1				
ULSD	**0.0921**	0.8063	1			
RBOB	**0.1352**	0.6642	0.7029	1		
Brent	**0.1046**	0.8767	0.8756	0.7212	1	
Gasoil	**0.1868**	0.5935	0.6705	0.5004	0.6628	1

Panel D	HMGO	WTI	ULSD	RBOB	Brent	Gasoil
HMGO	1					
WTI	**0.1511**	1				
ULSD	**0.1722**	0.8063	1			
RBOB	**0.1258**	0.6642	0.7029	1		
Brent	**0.1723**	0.8767	0.8756	0.7212	1	
Gasoil	**0.2795**	0.5935	0.6705	0.5004	0.6628	1

Note : Each panel displays unconditional correlations between a bunker return and five futures returns. Values of interest are reported in bold.

Source: Author's computations.

6.1.2 Univariate GARCH results

As noted above, one needs to begin with fitting the univariate GARCH models first. We also decided to incorporate AR(1) component into the conditional mean equation based on the stationary ARMA model to eliminate a certain dependence in the return series. Following the notation of vanilla GARCH, we entertain AR(1)-GARCH(1,1):

$$\begin{aligned} r_t &= \psi_0 + \psi_1 r_{t-1} + \varepsilon_t, \\ \varepsilon_t &= \sqrt{h_t} z_t; \quad z_t \sim N(0,1), \\ h_t &= \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \end{aligned} \tag{6.2}$$

and AR(1)-GJR-GARCH(1,1,1):

$$\begin{aligned} r_t &= \psi_0 + \psi_1 r_{t-1} + \varepsilon_t, \\ \varepsilon_t &= \sqrt{h_t} z_t; \quad z_t \sim N(0,1), \\ h_t &= \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 I_{[\varepsilon_{t-1}<0]} + \beta_1 h_{t-1}. \end{aligned} \tag{6.3}$$

The stationarity condition for AR(m) could be consulted in Enders (2014) because we only need AR(1), and thus we do not report the general requirements through lag operators. That being the case, it suffices $|\psi_1| < 1$ for AR(1) to hold. MA(n) process is always covariance stationary (Tsay, 2010).

Tables 6.3 and 6.4 present the coefficient estimates. Both variants of the model yield insignificant intercept parameters ψ_0 and statistically significant slope parameters ψ_1 for all commodities in the first autoregressive equation. Thereafter, we specify variance equations under the distributional assumption of normality. All of the constant terms ω, representing the long-run variance, are significant at the conventional significance levels. As outlined in Chapter 4, the conditions for covariance stationary process with a positive conditional variance hold in both symmetric and asymmetric instances. The significance of α_1 and β_1 points to the clustering presence. The coefficient of short-term persistence α_1 is considerably small compared to the long-term persistence coefficient of β_1, which means that shocks and the arrival of new information have a longer lasting effect on the volatility, and hence dominate the process. To distinguish between the models, γ_1 term dependent on the sign of past innovations is not uniformly significant. One can differentiate between negative and positive past shocks only when dealing with all futures contracts, Rotterdam bunkers and HMGO. Other commodities do not exhibit the leverage effect. The coefficient is positive, suggesting that the model can indeed capture the asymmetric property of volatility. The term ranges from 0.042 to 0.095, being greater than its symmetric analogue α_1 with the exception of RBOB.

The very right parts of Tables 6.3 and 6.4 show diagnostic tests. In the same way as in the previous chapter, the Ljung-Box test and the ARCH-LM test, both of order one and ten, are computed on the GARCH filtered squared standardized residuals. The use of both lags is justified to make sure that potential significant correlations are not washed out by insignificant autocorrelations at higher lags. However, this time, the statistics show that the residuals are *not* significantly different from zero. Formally, we fail to reject the null hypothesis of no serial autocorrelation and no ARCH effects, respectively. It can thus be stated that AR(1)-GARCH(1,1) and AR(1)-GJR-GARCH(1,1,1) models sufficiently capture the presence of conditional heteroskedasticity in our time series.

6.1.3 Multivariate GARCH results

Since we have correctly estimated the individual volatility processes, the vectors of standardized residuals $\epsilon_{i,t} = r_{i,t}/\sqrt{h_{i,t}}$ help us to estimate correlation processes in Equation 4.23. Tables 6.5–6.8 report (A)DCC results. Dependence on lagged innovations as measured by a is very small, the figures are even lower than in the univariate case of α_1, but still they are significant. Evidence of strong covariance persistence could be inferred from high values of b ranging from 0.84 to 0.99, yielding the significance at the 1% level in all 80 correlations. Despite the abundance of leverage effect in conditional volatilities, asymmetries in correlations are not common. The asymmetric term g is positive and significant for only five pairwise correlations out of 40, and that is, HMGO-ULSD at the 1% significance level; RMGO-ULSD, RIFO-Brent and RIFO-Gasoil at the 5% significance level, and HMGO-Gasoil at the 10% significance level. This means that the correlations are higher when prices of both commodities in a pair decrease rather than increase. Having estimated all models and verified regularity conditions described in Chapter 5, we may thus conclude that the univariate GARCH models capture any remaining autocorrelations. They are adequate for fat-tailed and volatility clustering in our time series and are able to capture the dynamics of returns of each energy asset just as MGARCH models for each pair of symmetric and asymmetric correlations.

Table 6.3: AR(1)-GARCH(1,1) results

	ψ_0	ψ_1	ω	α_1	β_1	Q^2		ARCH	
						(1)	(10)	(1)	(10)
WTI	0.000249 (0.717)	-0.029290* (-2.604)	0.000004** (3.616)	0.086363*** (2.584)	0.911887*** (84.221)	1.51	3.97	1.27	18.43
ULSD	-0.000009 (-0.030)	-0.022039* (-2.030)	0.000004** (2.369)	0.067620*** (5.852)	0.926457** (72.970)	3.89	4.89	1.75	8.24
RBOB	0.00006 (0.145)	-0.012173** (-2.610)	0.000002** (2.061)	0.116759*** (3.246)	0.858813*** (19.671)	1.10	2.12	1.09	5.23
Brent	0.000227 (0.707)	-0.032324* (-2.599)	0.000003** (1.961)	0.081126*** (6.882)	0.917870** (75.802)	1.25	11.92	1.49	10.87
Gasoil	0.000045 (0.111)	0.034670** (2.692)	0.000001** (3.464)	0.049318*** (3.023)	0.949680*** (57.986)	1.58	5.37	2.29	10.99
RIFO	0.000108 (0.128)	0.065161** (2.475)	0.000001*** (2.429)	0.065780*** (2.768)	0.933202*** (37.245)	1.80	3.40	2.07	6.30
RMGO	0.000019 (0.064)	0.040158** (2.002)	0.000001*** (2.029)	0.061074*** (5.611)	0.937926*** (83.012)	4.87	9.22	1.75	13.93
SIFO	0.000155 (0.489)	0.046911* (2.221)	0.000001*** (3.043)	0.055583*** (3.835)	0.933417*** (52.743)	2.31	5.68	1.73	16.25
SMGO	0.00004 (0.188)	-0.016074* (-1.937)	0.000001*** (2.014)	0.058479*** (2.069)	0.930521*** (32.438)	1.33	4.39	2.23	12.66
FIFO	0.000207 (0.906)	-0.010357* (-2.538)	0.000001*** (2.513)	0.057983*** (4.837)	0.941017*** (75.707)	2.45	3.94	1.95	13.26
FMGO	-0.000087 (-0.144)	-0.197844** (2.014)	0.000002*** (2.031)	0.067787*** (5.707)	0.921213*** (36.097)	1.18	5.02	1.35	10.36
HIFO	0.000095 (0.349)	-0.097170* (-2.390)	0.000001*** (2.076)	0.062288*** (4.429)	0.936712*** (65.319)	4.50	6.85	1.90	12.32
HMGO	0.000052 (0.265)	-0.091529*** (-6.317)	0.000002** (2.010)	0.070431*** (2.285)	0.928565*** (71.643)	1.24	3.18	1.89	12.99

Note : Numbers in parentheses are robust t-statistics. $Q^2(I)$ stands for the Ljung-Box test of order I computed on the squared standardized residuals of respective commodities. The ARCH(I) test denotes the ARCH-LM test of order I for the standardized residuals of respective commodities. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.

Source: Author's computations.

Table 6.4: AR(1)-GJR-GARCH(1,1,1) results

	ψ_0	ψ_1	ω	α_1	β_1	γ_1	Q^2		ARCH	
							(1)	(10)	(1)	(10)
WTI	-0.000217 (-0.648)	-0.034683* (-2.808)	0.000003*** (3.341)	0.013568** (2.872)	0.935802*** (20.808)	0.095159** (2.137)	2.18	2.38	1.53	7.49
ULSD	-0.000198 (-0.659)	-0.024922* (-2.062)	0.000003*** (3.292)	0.038184*** (3.511)	0.931315*** (69.384)	0.048080** (2.484)	3.82	4.75	2.85	7.60
RBOB	-0.000139 (-0.358)	-0.019422* (-1.978)	0.000019*** (4.879)	0.080255*** (5.749)	0.865143*** (53.078)	0.061073*** (3.388)	1.56	3.78	1.10	12.30
Brent	-0.000189 (-0.577)	-0.038073** (-2.478)	0.000003** (2.176)	0.017387** (2.801)	0.937141*** (65.924)	0.084556* (1.248)	1.42	11.36	1.66	18.49
Gasoil	-0.000281 (-0.997)	-0.038142** (2.069)	0.000001** (2.365)	0.011351** (2.002)	0.954753*** (188.758)	0.048470*** (6.680)	0.28	3.80	1.41	13.07
RIFO	-0.000049 (-0.065)	0.063002*** (2.923)	0.000001* (2.725)	0.035483*** (3.434)	0.942343*** (70.723)	0.042349*** (1.078)	0.83	2.91	2.00	4.98
RMGO	-0.000209 (-0.756)	0.033756* (2.676)	0.000001** (3.229)	0.020829*** (2.010)	0.955512*** (87.703)	0.045318*** (3.499)	2.70	11.74	1.07	3.28
SIFO	0.000022 (-0.282)	0.071620* (2.000475)	0.000001* (2.0004)	0.042977*** (2.819)	0.940040*** (56.967)	0.031966 (0.209)	0.34	2.41	1.31	11.83
SMGO	-0.000093 (-0.035)	-0.013604* (-2.642)	0.000001* (1.994)	0.034021*** (2.652)	0.948175*** (41.655)	0.033608 (0.470)	2.21	11.41	2.16	11.67
FIFO	0.000100 (-0.100)	-0.011523* (-2.377)	0.000001* (2.031)	0.030933*** (2.696)	0.948137*** (76.742)	0.039859 (1.769)	2.62	3.71	1.54	12.27
FMGO	-0.000080 (-0.157)	-0.197751** (-2.050)	0.000001* (2.027)	0.077027*** (6.740)	0.927199*** (91.479)	-0.010453 (-1.724)	1.01	2.04	1.73	12.14
HIFO	-0.000066 (-0.047)	-0.011286* (-2.454)	0.000001* (2.023)	0.036653*** (2.770)	0.944510*** (42.619)	0.035674 (0.996)	4.76	7.27	2.88	16.72
HMGO	-0.000119 (-0.567)	-0.086959*** (-4.569)	0.000002** (2.813)	0.038696*** (2.851)	0.932546*** (48.300)	0.055035** (2.444)	0.36	4.09	1.85	14.74

Note : Numbers in parentheses are robust t-statistics.$Q^2(I)$ stands for the Ljung-Box test of order I computed on the squared standardized residuals of respective commodities. The ARCH(I) test denotes the ARCH-LM test of order I for the standardized residuals of respective commodities. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.

Source: Author's computations.

Table 6.5: Multivariate GARCH results – Rotterdam

Panel A: RIFO	Futures	Model	*a*	*b*	*g*
	WTI	DCC	0.005098*** (2.439)	0.869436*** (28.014)	
	WTI	ADCC	0.000239** (1.998)	0.883031*** (39.577)	0.015175 (0.426)
	ULSD	DCC	0.013729** (2.662)	0.925600*** (111.320)	
	ULSD	ADCC	0.000725** (2.039)	0.904447*** (25.805)	0.020000 (0.709)
	RBOB	DCC	0.003517** (2.462)	0.915625*** (95.704)	
	RBOB	ADCC	0.003821** (3.472)	0.933469*** (78.115)	0.010022 (0.000045)
	Brent	DCC	0.016780** (2.980)	0.844751*** (35.225)	
	Brent	ADCC	0.001985* (1.994)	0.946222*** (134.399)	0.035791** (2.640)
	Gasoil	DCC	0.023892** (2.978)	0.967761*** (27.009)	
	Gasoil	ADCC	0.006753** (2.137)	0.936003*** (86.181)	0.923216** (122.380)
Panel B: RMGO	Futures	Model	*a*	*b*	*g*
	WTI	DCC	0.004836** (2.516)	0.891253*** (130.7587)	
	WTI	ADCC	0.004011** (3.708)	0.993408*** (74.016)	0.001102 (0.754)
	ULSD	DCC	0.004689** (2.122)	0.929856*** (56.684)	
	ULSD	ADCC	0.004466** (2.219)	0.939333*** (73.752)	0.014280** (2.916)
	RBOB	DCC	0.003625** (2.261)	0.994708*** (151.721)	
	RBOB	ADCC	0.003741** (2.362)	0.949551*** (38.748)	0.000821 (0.738)
	Brent	DCC	0.006065** (2.988)	0.989224*** (56.912)	
	Brent	ADCC	0.005574** (3.229)	0.970492*** (76.623)	0.001828 (0.731)
	Gasoil	DCC	0.004575*** (2.983)	0.953690*** (67.501)	
	Gasoil	ADCC	0.004539*** (3.377)	0.959218*** (149.167)	0.000574 (0.577)

Note: *Panel A* displays coefficient estimates for HFSO and the corresponding futures contract while *Panel B* displays coefficient estimates for LSFO and the corresponding futures contract. Numbers in parentheses are robust t-statistics. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.

Table 6.6: Multivariate GARCH results – Singapore

Panel A: SIFO	Futures	Model	*a*	*b*	*g*
	WTI	DCC	0.002981*** (2.663)	0.955459*** (134.929)	
	WTI	ADCC	0.003122** (3.409)	0.995199*** (101.011)	0.000110 (0.036)
	ULSD	DCC	0.009754*** (3.106)	0.915830*** (82.828)	
	ULSD	ADCC	0.004523** (2.002)	0.946723*** (39.256)	0.057244 (1.650)
	RBOB	DCC	0.013024** (3.544)	0.902333*** (21.722)	
	RBOB	ADCC	0.008929** 2.607)	0.890168*** (33.876)	0.007942 (0.124044)
	Brent	DCC	0.005104** (2.065)	0.992427*** (123.071)	
	Brent	ADCC	0.005653** (2.642)	0.960669*** (88.175)	0.000121 (0.026)
	Gasoil	DCC	0.005058*** (2.166)	0.993005*** (159.074)	
	Gasoil	ADCC	0.005060*** (3.124)	0.929293*** (160.555)	0.001298 (0.056)
Panel B: SMGO	Futures	Model	*a*	*b*	*g*
	WTI	DCC	0.002985*** (3.804)	0.975621*** (83.366)	
	WTI	ADCC	0.004590** (2.201)	0.987703*** (27.058)	0.024510 (0.630)
	ULSD	DCC	0.003386** (2.917)	0.940002*** (137.497)	
	ULSD	ADCC	0.003584** (3.815)	0.932939*** (133.668)	0.000567 (0.427)
	RBOB	DCC	0.009643** (2.989)	0.940397*** (86.902)	
	RBOB	ADCC	0.003210*** (2.710)	0.880081*** (78.243)	0.020291 (0.696)
	Brent	DCC	0.004940*** (2.445)	0.993234*** (196.639)	
	Brent	ADCC	0.005323*** (2.554)	0.912258*** (128.187)	0.000660 (0.473)
	Gasoil	DCC	0.005348*** (4.215)	0.902831*** (43.689)	
	Gasoil	ADCC	0.005286*** (3.879)	0.982805*** (158.659)	0.000344 (0.282)

Note: *Panel A* displays coefficient estimates for HFSO and the corresponding futures contract while *Panel B* displays coefficient estimates for LSFO and the corresponding futures contract. Numbers in parentheses are robust t-statistics. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.

Table 6.7: Multivariate GARCH results – Fujairah

Panel A: FIFO	Futures	Model	a	b	g
	WTI	DCC	0.002046*** (2.456)	0.960616*** (112.363)	
	WTI	ADCC	0.001837*** (3.535)	0.969109*** (103.540236)	0.000235 (0.092)
	ULSD	DCC	0.004922*** (2.828)	0.927535*** (27.544)	
	ULSD	ADCC	0.005281** (2.672)	0.934375*** (28.357695)	0.000428 (0.033)
	RBOB	DCC	0.012293** (3.909)	0.916369*** (37.009)	
	RBOB	ADCC	0.011758** 2.497)	0.923864*** (30.867)	0.000114 (0.028)
	Brent	DCC	0.002212*** (2.810)	0.916114*** (74.785)	
	Brent	ADCC	0.002209*** (2.578)	0.975723*** (82.628)	0.000625 (0.025)
	Gasoil	DCC	0.004779** (2.832)	0.993952*** (122.561)	
	Gasoil	ADCC	0.004721*** (4.597)	0.933877*** (169.452)	0.000379 (0.076)
Panel B: FMGO	Futures	Model	a	b	g
	WTI	DCC	0.001761** (2.344)	0.976294*** (107.163)	
	WTI	ADCC	0.001960** (2.412)	0.965945*** (56.512)	0.000696 (0.092)
	ULSD	DCC	0.007210** (1.985)	0.981542*** (37.225)	
	ULSD	ADCC	0.007100** (2.071)	0.982872*** (29.261)	0.000188 (0.101)
	RBOB	DCC	0.002836*** (3.890)	0.915138*** (57.403)	
	RBOB	ADCC	0.002920*** (1.992)	0.905036*** (73.343)	0.000109 (0.131)
	Brent	DCC	0.003080** (2.309)	0.941649*** (97.991)	
	Brent	ADCC	0.003536** (2.404)	0.923868*** (93.182)	0.000827 (0.066)
	Gasoil	DCC	0.003550*** (2.659)	0.905811*** (79.456)	
	Gasoil	ADCC	0.003379*** (2.759)	0.995952*** (118.486)	0.000451 (0.045)

Note: *Panel A* displays coefficient estimates for HFSO and the corresponding futures contract while *Panel B* displays coefficient estimates for LSFO and the corresponding futures contract. Numbers in parentheses are robust t-statistics. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.

Table 6.8: Multivariate GARCH results – Houston

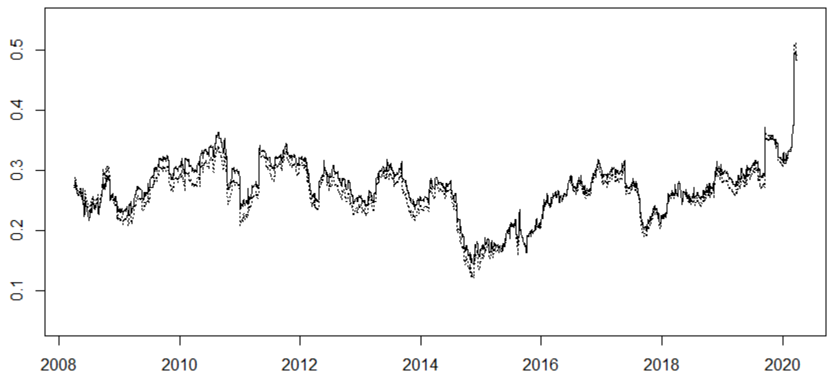
Panel A: HIFO	Futures	Model	a	b	g
	WTI	DCC	0.011113*** (3.822)	0.988624*** (150.705)	
	WTI	ADCC	0.010623*** (3.962)	0.987391*** (128.412)	0.003570 (1.149197)
	ULSD	DCC	0.011007*** (3.843)	0.928707*** (84.529)	
	ULSD	ADCC	0.010160*** (3.858)	0.938051*** (31.371)	0.003396 (1.110)
	RBOB	DCC	0.007230*** (3.588)	0.962419*** (93.522)	
	RBOB	ADCC	0.006859*** (3.599)	0.852267*** (113.036)	0.001129 (0.699)
	Brent	DCC	0.012025*** (3.516)	0.987718*** (78.958)	
	Brent	ADCC	0.010394*** (3.786)	0.877563*** (87.047)	0.004725 (1.150)
	Gasoil	DCC	0.015421*** (4.545)	0.924247*** (168.262)	
	Gasoil	ADCC	0.014779*** (4.677)	0.953384*** (69.338)	0.003290 (1.872)
Panel B: HMGO	Futures	Model	a	b	g
	WTI	DCC	0.010181*** (4.218)	0.989209*** (118.148)	
	WTI	ADCC	0.009886*** (3.887)	0.888658*** (24.520)	0.002842 (1.300)
	ULSD	DCC	0.010749*** (5.881)	0.951542*** (37.225)	
	ULSD	ADCC	0.010154*** (4.505)	0.988881*** (97.146)	0.089001*** (3.063)
	RBOB	DCC	0.022178** (2.529)	0.902108*** (57.638)	
	RBOB	ADCC	0.00517*** (2.887)	0.923416*** (40.299)	0.001075 (0.755)
	Brent	DCC	0.010742*** (4.600)	0.989227*** (133.707)	
	Brent	ADCC	0.009764*** (4.371)	0.958825*** (158.882)	0.003468 (1.483)
	Gasoil	DCC	0.015290*** (5.213)	0.984710*** (107.833)	
	Gasoil	ADCC	0.014590*** (5.232)	0.913754*** (81.149)	0.041330* (1.149)

Note: *Panel A* displays coefficient estimates for HFSO and the corresponding futures contract while *Panel B* displays coefficient estimates for LSFO and the corresponding futures contract. Numbers in parentheses are robust t-statistics. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.

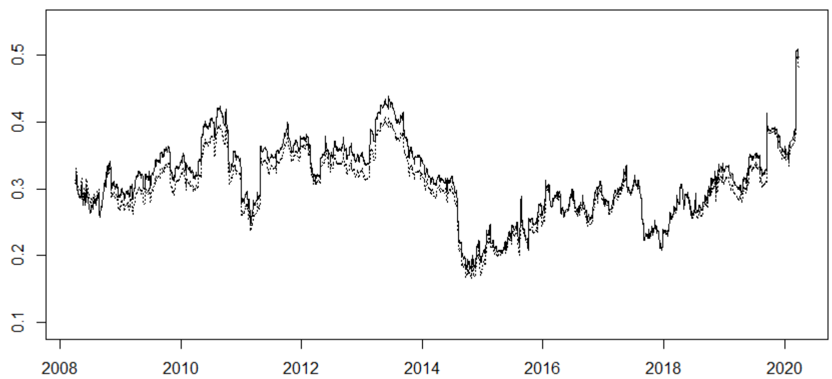
To illustrate how correlations evolve through time, we make use of the graphical analysis. Considering it case by case through the whole sample would be too chaotic. Correlations from the DCC model usually mimic the ADCC model (or vice versa) so we try to detect certain phases where the differences between the models are more contoured. For illustration, Figure 6.1 presents correlations between Rotterdam bunkers and ULSD from 2008 to 2020. One particular feature is apparent. Rising correlations between selected pairs of commodities indicate a recession, which makes our *Hypothesis 2* perfectly valid. The correlation process continues in an upward manner as negative effects disseminate through time. Correlations do not seem to increase from the time when the housing bubble burst since the commodities are related in a similar way around 30%. There is not a great variability between HFSOs and LSFOs in terms of the strength of relation with ULSD.

Figure 6.1: Selected dynamic conditional correlations

(a) Correlations between RIFO and ULSD



(b) Correlations between RMGO and ULSD



Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

In addition, since the symmetric model coincides with its asymmetric counterpart in more instances, we want to illustrate how separate time segments of dynamic conditional correlations differentiate such a feature. These results are similar for the majority of correlations under our research so the discussion could mediate general conclusions. To demonstrate the point, we granulate the time span of our analysis into three periods in Figure 6.2. The first depiction (703 observations) shows the tail end of the subprime mortgage crisis and subsequent years of recovery. We can see somewhat turbulent correlations pointing to the instability of fuel oil alternatives as a useful hedging instrument besides other issues. The second picture (1277 observations) shows relatively calm periods of 2011 through 2014 till the 2015 commodity crash when correlations started to rise again at the seemingly common level for the bunkers. There is no apparent distinction between DCC models. The last picture (1093 observations) gives an account of yet very peculiar times. We believe that it provides the most illuminating information with regard to the different behavior of the models as well as it covers the recovery phase, market tranquility, IMO 2020 and the onset of the global coronavirus outbreak. Consequently, all corresponding figures in the Appendix[1] are constructed with this time window since the whole sample would be far too restrictive in that we would have to compromise on the readability and distinct patterns of correlations. The y-axis corresponds to the strength of correlations, and thus varies from pairs to pairs.

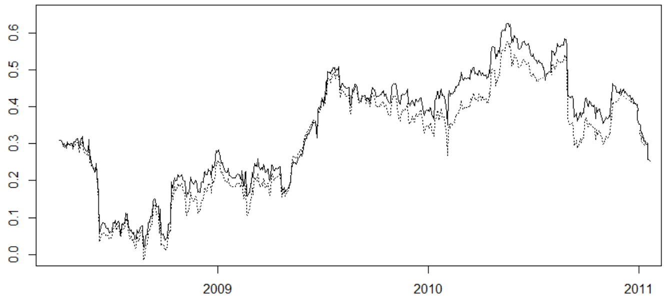
In general, we can notice a sharp rise and fall in prices regardless of the correlations and ports. This fact reinforces *Hypothesis 1* because there is literally heterogeneity in returns of petroleum-refined products. As might be expected, the levels of economic and political stability change and market participants respond accordingly in pricing financial instruments. It is guaranteed that we can track diverse (a)symmetric linkages between energy commodities. In addition, attention has already been drawn to what extent correlations are crucial in many financial decisions. However much important aspect, this has been largely ignored in the context of the marine and shipping industry. Therefore, we proceed with a detailed analysis of bunker-futures correlations.

It should be mentioned that resulting correlations depend on standardized residuals. If they move in sync, the correlations are amplified and later pulled back over time due to total information absorption. The opposite movements occur when residuals progress adversely as time passes (Bhatia and Mitra, 2018).

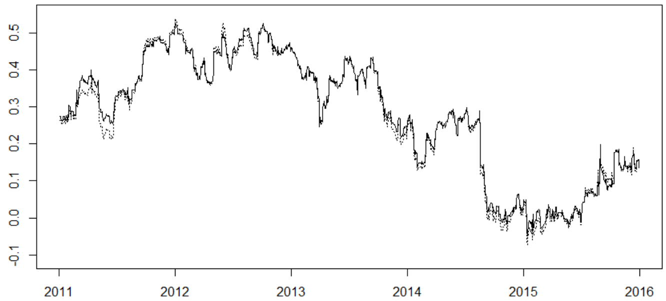
1 To save space, those correlations depicted herein are not included in the Appendix.

Figure 6.2: Segments of dynamic conditional correlations between HMGO and ULSD

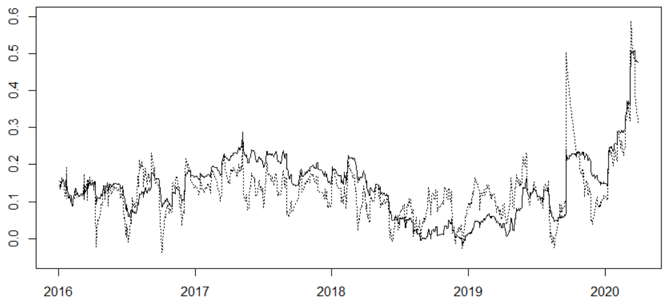
(a) 2008–2011



(b) 2012–2015



(c) 2016–2020



Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Let us now present basic features of dynamic conditional correlations. Starting with Figure A.3, it becomes obvious that WTI, Brent and gasoil are the most volatile commodities when combined with RIFO, estimating the level of interconnectedness at 40%. While RBOB may not display unpredictable sways, the correlations are lowest in the range of 2% – 45%, mostly around 20%. It can be assumed that they are weakened after the commodity price shock. The DCC and ADCC models follow more or less the same direction with the irregularity in the case of RBOB going through 2018. Moreover, Figure A.4 reveals that correlations around 35% are most prevalent for Rotterdam bunkers. Further to our previous comments, RMGO appears to correlate with RBOB less turbulently in comparison to other futures contracts and there are no clear differences between the two models as they mostly coincide, suggesting almost zero asymmetry in energy products. In this case, visual inspection does not allow us to recommend either HSFOs or LSFOs as a better choice.

Second, we now turn to Singapore spot contracts. The first intriguing observation in Figure A.5 is that correlations fluctuate heavily and they are noticeably lower in contrast with the Rotterdam case taking mostly values around 15% to 30%. The immediate post-2015 crisis period is not perceptible with the recovery period, which could be taken as evidence that the interrelationship between bunkers and futures contracts at more distant ports from the exchanges decreases. The conditional correlations models do not differentiate between positive and negative innovations for HSFOs. Their ability to respond to bad and positive shocks is more pronounced for LSFOs which could be observed in Figure A.6. However, the correlations between SMGO and derivatives are even lower reaching usually the value of 20%. Contrary to common findings, their development is relatively smooth, implying no abrupt changes particularly with regard to European contracts.

Figures A.7 and A.8 give the lowest correlations across the whole globe. The most volatile bunkers prior to the inception of the IMO 2020 are LSFOs. They are generally in the range of 10% to 20% aside from the case of RBOB where correlations are even negative. A time-varying nature captured by the symmetric and asymmetric MGARCH models is usually identical as we cannot discern more striking features of either of the two. It can thus be stated that the spot-futures conditional VCM responds almost equally likely to positive and negative innovations in a long-run horizon. The correlations obviously reached their peak in 2020 with the maximum value of 40% that could be regarded as a medium degree of interconnectedness between two assets, which is the highest synchronicity the commodities gain throughout the whole sample from 2008 through 2020. There is no such thing as moderate volatility under normal times. Patterns of correlations between bunker contracts and either ULSD, Brent or gasoil point to the possible better hedging potential in the asset allocation framework.

Finally, careful reader might notice in Figures A.9 and A.10 that the bunker-RBOB pairs yield negative interdependence falling as low as -20%, and hence indicating the least favourable contract in portfolio protection strategy. It could be observed that asymmetric responses to volatility and correlations are particularly more contoured in the LSFOs cases since the immediate months preceding the sulphur cap regulations saw increased correlations between MGOs and futures contracts, signalizing a certain abrupt shock to the global economy, one of the many in the modern history. The upward trajectory draws a level of more than 80% with the values usually ranging from 10% to 30%. We can see an evident decline in correlations in the second half of 2019, possibly due to the trade wars thwarting a trend of stable nexus between selected commodities. Once more, the inclusion of the asymmetric term into the DCC does not always translate into a more exhaustive analysis since it is significant in rare cases.

All 80 dynamic conditional correlations have one thing in common. They spike upward due to specific market events. To further elaborate on this, we can observe the strengthening of correlations in early 2020 due to the fall in prices of petroleum-refined products as a consequence of an oil price war between Russia and Saudi Arabia. The demand for these commodities later shattered, posing a major threat for companies involved in oil extraction and distribution. The imposed travel restrictions also led to sunk in prices and supplying excess oil to the world saw a greater correlation tightening during stress conditions as high as 80%. While not accounted, this outstripped the GFC as an entirely unprecedented situation with no parallels in history but the Great Depression owing to both economic but mainly social impacts.

6.2 The in-sample performance

Initially, we divide the whole sample period into two subperiods. The former class covers the period from April 2, 2008, to February 25, 2013 (1250 data points), the latter from February 26, 2013, to March 30, 2020 (1823 data points). After that, we estimate the models' parameters with the in-sample data and then use them to forecast future hedge ratios as given by Equation 4.30. It must be borne in mind that the hedge duration is equivalent to the daily data frequency.

First, the unhedged position is represented by the spot market so that we could compare the competing models and their hedging effectiveness. Second, naïve hedge can also be classified among static hedging strategies that maintain

OHR constant over time. It involves a trader with a long position in the spot market who should simultaneously sell the same quantity of futures contracts, assuming hedge ratio $\lambda_t^* = 1$. For that reason, some studies refer to it as the one-to-one ratio. This is the simplest way to hedge risk.

The third case revolves around the OLS method which serves us as a fine representative of a conventional hedge. At this point, it is necessary to comment on the regression results that are given in Tables A.2 and A.3 in the Appendix since we focus more on conditional models and want to keep the flow of models going. Nonetheless, all panels show a significant estimated parameter λ on the futures return series at the 1% significance level. The intercept parameter is not statistically significant in either of the 40 examples, and thus not significantly different from zero. The parameter shall be retained in the regression based on Equation 4.31 in order not to change the response of the independent variables on the dependent ones even if the intercept is not substantively interpretable. Positive values indicate that there are positive correlations between commodities. The figures range from 0.0596 to 0.4467. This suggests that the ratio between the number of futures contracts used for hedging and the related spot position is small for the bunkers of Fujairah whereas fuel oils that are more closely connected to the exchanges, and that is Rotterdam and Houston, exhibit much greater values.

All in all, it is reasonably expected that the model cannot properly capture heteroskedasticity in our data. The Breusch-Pagan test (Breusch and Pagan, 1979) assumes linear dependence of variance on the independent variables with the null hypothesis of homoskedasticity. As the residuals from the OLS regression are dependent on all independent variables, we reject the null hypothesis in favour of present heteroskedasticity, which is a sign of potential weakness of the static hedge ratios. Similarly, the Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978) builds on the simple idea of existing autocorrelation in the regression with weakly exogenous independent variables. The null hypothesis of no serial correlation is rejected at the conventional significance levels violating classical linear model assumptions while keeping unbiased and consistent estimator. All regressions display low adjusted R-squared, which may be put down to lower correlation between energy products marking the OLS technique as below the standard and deeming it potentially unreliable. The specification of the model does not produce good explanatory power as it cannot account for volatility of the dependent variable in an appropriate manner. Therefore, the coefficient of determination accentuates more elaborate approach towards the time-series analysis.

Tractability of MGARCH models allows us to properly account for a parameterization of conditional second moments, and thus systematically tracing variations in our data. Following MGARCH estimation of separate specification of variance and correlations in a hierarchical way, we can extract inputs for variance reduction. Non-constant ratios are calculated as the mean of 1250 hedge ratios for a given combination of futures and spot position which translates into 80 individually distinct ratios within our sample. The square variance-covariance matrices (VCM) for both in- and out-of-sample examples are available from the authors upon request.

Table 6.9 reports four different types of hedge ratios based on naïve hedge, OLS, DCC and ADCC-GARCH models. From a practical point of view, the in-sample performance of the respective models does not make generalizations possible; nevertheless, several features could be observed. Disregarding naïve classification, the pairs of a spot contract and WTI, ULSD, RBOB or Brent convey that hedge ratios based on the OLS are usually the lowest while ADCC model provides the highest figures. The exception seems to be ULSD where the DCC model is able to outperform its asymmetric counterpart. Contrary, gasoil and bunker fuels produce the highest hedge ratios taken as a whole and with the increasing level of specification of the econometric models they become weaker. In general, the asymmetric MGARCH model is not necessarily better than the symmetric case, stemming from the fact that its estimation usually led to the insignificant leverage term even at the 10% significance level. The striking feature is that all models yield a very similar result, which signals important implications discussed in the later stages of this chapter.

Hedging effectiveness for each strategy, and by extension a convenient model, can be found in Tables 6.10 and 6.11. A direct comparison between hedge ratios will give us finally some information worth thinking seriously about with regard to the distinction between HSFOs and LSFOs and their associated behavior with the global futures market. Naïve hedge unsurprisingly gives the lowest percentage variance reduction reaching as far as -98.05%. Since all of its figures are negative apart from the RMGO-gasoil pair, it may be put forward that using the 1-to-1 hedge ratio leaves an undesirable outcome for market participants and the value of a portfolio investment shall be left unprotected against any changes in the bunker prices since it utterly increases the variance. We use this method purely as a source of comparison for other methods as it is not commonly used in energy markets and the associated risk management.

Besides that, one can imagine that having a portfolio of assets unprotected, i.e. the unhedged case, produces the highest variance with no differences across all commodities. A subsequent description omits naïve diversification since we want to make sure whether hedging using the proposed models in Chapter 4 is effective or not.

The results presented in *Panels A* and *B* in Table 6.10 raise interesting suggestions. Despite moderately different, Rotterdam LSFOs appear to have higher hedging effectiveness, varying from 3.80% to 29.37%, in contrast to HSFOs whose HEI ranges from 3.42% to 15.10%. What is more, the value of 29.37% represents the highest variance reduction across all four ports for hedging RMGO and gasoil futures. Irrespective of the combination and ports, gasoil is the best hedging instrument, and can thus be perceived as the most suitable cross hedge for the cash position. *Panels C* and *D* show Singapore spot contracts and their usefulness in mitigating price risk. In addition to what has already been mentioned, HSFOs ($0.66\% - 11.50\%$) do not display as high degree of hedging effectiveness as LSFOs ($1.60\% - 14.22\%$) reaching very low levels particularly in terms of the WTI pairings. Further, we can easily observe such trend in *Panels A* and *B* in Table 6.11, propounding that fuels used in more distant ports from the exchanges show signs of lower variance reduction in offsetting potential losses as a result of very volatile price fluctuations. Representing a relatively new bunker marker, Fujairah spot contracts exhibit much the same HEI as Singapore which lies between 2.36% and 12.35%, and 2.76% and 9.60% for HSFOs and LSFOs, respectively. Somewhat surprisingly, the reverse trend can be seen for Houston port where the position of IFO in futures contracts reduces variance from 4.55% up to 13.84% contrasting MGO's limits of 1.29% and 11.80%.

To sum up, the results are fairly uniform and for that reason, we can generalize some results as the pattern is visible. The MGARCH models may reduce the variance of returns more than the OLS approach in some instances, such as FIFO-gasoil or HIFO-ULSD; however, it cannot be taken as a convincing argument that they are better than OLS hedge ratios due to their utmost similarity which is apparent in every panel of both tables. It can be inferred that OLS, DCC and ADCC have an almost identical impact on variance of the portfolio, and thus its reduction against an unhedged position. In terms of the efficiency of the MVHR paradigm, this result may largely be a reflection of the dependence assumption between spot and futures contracts that is far too volatile when analyzing daily data.

Table 6.9: In-sample hedge ratios

Panel A: RIFO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel E: FIFO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.16390	0.24845	0.18764	0.23121	0.44677		OLS	0.11707	0.18944	0.13966	0.16193	0.34709
	DCC	0.20695	0.25634	0.19140	0.25657	0.43102		DCC	0.15243	0.19295	0.14611	0.18949	0.34416
	ADCC	0.22224	0.24774	0.19931	0.25325	0.42908		ADCC	0.15911	0.18911	0.14803	0.18899	0.34305
Panel B: RMGO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel F: FMGO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.14351	0.25040	0.17470	0.20500	0.50900		OLS	0.05960	0.08298	0.05971	0.07345	0.14540
	DCC	0.20053	0.26862	0.19672	0.25727	0.49559		DCC	0.05768	0.07444	0.05448	0.07405	0.13091
	ADCC	0.20021	0.26227	0.19411	0.25755	0.49521		ADCC	0.06629	0.07386	0.06151	0.07748	0.13476
Panel C: SIFO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel G: HIFO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.08972	0.14769	0.11169	0.13381	0.35658		OLS	0.18907	0.28439	0.20382	0.26637	0.37897
	DCC	0.14382	0.17362	0.12889	0.18154	0.35989		DCC	0.26848	0.34012	0.23435	0.33801	0.40512
	ADCC	0.15504	0.16925	0.13191	0.18088	0.35907		ADCC	0.29509	0.37145	0.23851	0.36525	0.42670
Panel D: SMGO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel H: HMGO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.08914	0.14810	0.09603	0.13390	0.32230		OLS	0.13080	0.19060	0.12250	0.16880	0.31540
	DCC	0.12387	0.14559	0.09851	0.15156	0.31128		DCC	0.21593	0.27051	0.15937	0.25350	0.41890
	ADCC	0.13262	0.14950	0.10989	0.16838	0.31425		ADCC	0.23798	0.29143	0.17941	0.27839	0.43729

Note: Panels report in-sample hedge ratios between respective bunkers and corresponding futures contracts. Non-constant hedge ratios are computed as the mean of hedge ratios within a given sample.
Source: Author's computations.

Table 6.10: In-sample hedging effectiveness – Rotterdam, Singapore

		WTI		ULSD		RBOB		Brent		Gasoil	
		Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction
Panel A: RIFO											
	Unhedged	0.00051		0.00051		0.00051		0.00051		0.00051	
	Naïve	0.00101	-98.05%	0.00074	-45.37%	0.00092	-80.99%	0.00082	-60.09%	0.00055	-8.06%
	OLS	0.00049	3.92%	0.00048	5.57%	0.00048	4.57%	0.00048	5.98%	0.00043	**15.10**%
	DCC	0.00049	3.65%	0.00048	5.56%	0.00048	4.56%	0.00048	5.90%	0.00043	15.08%
	ADCC	0.00049	3.42%	0.00048	5.57%	0.00048	4.54%	0.00048	5.92%	0.00043	15.07%
Panel B: RMGO											
	Unhedged	0.00034		0.00034		0.00034		0.00034		0.00034	
	Naïve	0.00067	-97.16%	0.00057	-67.44%	0.00066	-94.13%	0.00067	-98.81%	0.00033	2.04%
	OLS	0.00032	4.50%	0.00031	8.47%	0.00032	5.92%	0.00031	7.04%	0.00024	***29.37***%
	DCC	0.00032	3.79%	0.00031	8.43%	0.00032	5.83%	0.00031	6.58%	0.00024	29.35%
	ADCC	0.00032	3.80%	0.00031	8.45%	0.00032	5.85%	0.00031	6.58%	0.00024	29.35%
Panel C: SIFO											
	Unhedged	0.00043		0.00043		0.00043		0.00043		0.00043	
	Naïve	0.00064	-49.46%	0.00075	-75.93%	0.00084	-96.94%	0.00085	-97.84%	0.00054	-25.94%
	OLS	0.00042	1.40%	0.00042	2.35%	0.00042	1.93%	0.00042	2.39%	0.00038	**11.50**%
	DCC	0.00042	0.89%	0.00042	2.28%	0.00042	1.89%	0.00041	2.09%	0.00037	11.49%
	ADCC	0.00042	0.66%	0.00041	2.30%	0.00042	1.87%	0.00042	2.10%	0.00037	11.49%
Panel D: SMGO											
	Unhedged	0.00028		0.00028		0.00028		0.00028		0.00028	
	Naïve	0.00041	-45.07%	0.00050	-79.38%	0.00052	-83.25%	0.00044	-55.99%	0.00042	-48.63%
	OLS	0.00028	2.10%	0.00027	3.58%	0.00028	2.16%	0.00027	3.62%	0.00024	**14.22**%
	DCC	0.00028	1.78%	0.00027	3.58%	0.00028	2.16%	0.00027	3.56%	0.00024	14.20%
	ADCC	0.00028	1.60%	0.00027	3.58%	0.00028	2.12%	0.00027	3.39%	0.00024	14.21%

Note: Panels are structured according to spot contracts specifications. Variance is computed using Equations 4.34-4.37. Reduction represents hedging effectiveness in percentage terms according to Equation 4.33. Superior hedging performance for individual bunkers is reported in bold. On top of that, the single best hedging strategy is displayed in italics.
Source: Author's computations.

Table 6.11: In-sample hedging effectiveness – Fujairah, Houston

		WTI		ULSD		RBOB		Brent		Gasoil	
		Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction
Panel A: FIFO											
	Unhedged	0.00038		0.00038		0.00038		0.00038		0.00038	
	Naïve	0.00065	-71.72%	0.00066	-75.81%	0.00070	-86.73%	0.00072	-91.71%	0.00050	-31.32%
	OLS	0.00037	2.71%	0.00036	4.38%	0.00036	3.42%	0.00036	3.97%	0.00033	12.34%
	DCC	0.00036	2.46%	0.00036	4.38%	0.00036	3.42%	0.00036	3.85%	0.00033	12.34%
	ADCC	0.00037	2.36%	0.00036	4.38%	0.00036	3.41%	0.00036	3.86%	0.00033	**12.35**%
Panel B: FMGO											
	Unhedged	0.00009		0.00009		0.00009		0.00009		0.00009	
	Naïve	0.00014	-66.20%	0.00013	-51.97%	0.00017	-97.88%	0.00016	-90.74%	0.00015	-87.17%
	OLS	0.00008	3.11%	0.00008	3.73%	0.00008	2.78%	0.00008	3.62%	0.00007	**9.60**%
	DCC	0.00008	3.10%	0.00008	3.69%	0.00008	2.76%	0.00008	3.62%	0.00007	9.50%
	ADCC	0.00008	3.07%	0.00008	3.69%	0.00008	2.77%	0.00008	3.61%	0.00007	9.55%
Panel C: HIFO											
	Unhedged	0.00041		0.00041		0.00041		0.00041		0.00041	
	Naïve	0.00079	-96.95%	0.00060	-49.52%	0.00079	-97.82%	0.00067	-66.52%	0.00049	-23.33%
	OLS	0.00037	6.64%	0.00037	8.28%	0.00037	6.86%	0.00036	10.10%	0.00035	***13.84***%
	DCC	0.00038	5.47%	0.00037	8.93%	0.00037	6.71%	0.00036	9.37%	0.00035	13.77%
	ADCC	0.00038	4.55%	0.000367	8.42%	0.00037	6.66%	0.00037	8.71%	0.00035	13.62%
Panel D: HMGO											
	Unhedged	0.00033		0.00033		0.00033		0.00033		0.00033	
	Naïve	0.00062	-92.11%	0.00061	-87.47%	0.00062	-92.07%	0.00060	-86.49%	0.00047	-43.80%
	OLS	0.00031	3.91%	0.00031	5.13%	0.00032	3.05%	0.00031	4.99%	0.00029	**11.80**%
	DCC	0.00032	2.26%	0.00031	4.23%	0.00032	2.78%	0.00031	3.73%	0.00029	10.52%
	ADCC	0.00032	1.29%	0.00031	3.70%	0.00032	2.39%	0.00032	2.88%	0.00029	10.03%

Note: Panels are structured according to spot contracts specifications. Variance is computed using Equations 4.34-4.37. Reduction represents hedging effectiveness in percentage terms according to Equation 4.33. Superior hedging performance for individual bunkers is reported in bold. On top of that, the single best hedging strategy is displayed in italics.
Source: Author's computations.

6.3 The out-of-sample evidence

The aforementioned results yield only ex-ante information. Simply put, the in-sample performance does not necessarily mean that the models can do well in the future. What it provides is the past performance of the models. Their usefulness thus hinges on out-of-sample performance too as investors are more interested in what lies ahead.

The analysis of the out-of-sample performance needs to be conducted under a rolling-window approach. The procedure comprises two steps. The returns are assigned to a particular group based on the in-sample data for both volatility modelling and parameter estimating and the out-of-sample data for evaluating hedging or forecasting performance. The in-sample period is rolled forward by adding a new day and dropping the most distant day. In this manner, the sample size is fixed at 1250 days. We re-estimate the parameters each day to obtain the forecast of the next day's hedge ratio. Eventually, we have 1823 forecasts to derive one-step-ahead hedge ratios. Mathematically, it can be expressed in the following way (Fan et al., 2016). Using samples for $t = 1, \ldots, T$, we estimate the optimal hedge ratio $\{\hat{\lambda}_t^*\}_{t=1}^T$. The out-of-sample hedged portfolio returns can be calculated from $r_{T+1}^H = s_{T+1} - \hat{\lambda}_{T+1|T}^* f_{T+1}$, with $\hat{\lambda}_{T+1|T}^*$ being the one-step-ahead forecast of the OHR at time T. The observation for time $T+1$ is then included and the observation for time 1 is removed while keeping the size of the estimation sample fixed. Thereafter, using samples for $t = 2, \ldots, T+1$, we estimate the OHR $\hat{\lambda}_{T+2|T+1}^*$ and calculate $r_{T+2}^H = s_{T+2} - \hat{\lambda}_{T+2|T+1}^* f_{T+2}$. We proceed in a similar fashion to obtain the out-of-sample hedge ratio series $\left\{\hat{\lambda}_{t+1|t}^*\right\}_{t=T}^{T+K-1}$ and the out-of-sample hedged portfolio returns series $\{r_t^H\}_{t=T+1}^{T+K}$ for some K.

Analogically to the preceding subsection, we begin with the inspection of out-of-sample hedge ratios. Non-constant OHRs are computed as the mean of 1823 hedge ratios for the respective pair of commodities. Therefore, we ultimately report 80 different ratios based on VCM *within* our out-of-sample data. Allowing for time variation in our econometric structure does not automatically lead to a more optimal method. The highest hedge ratios based on the ADCC models are reported for RMGO and HMGO. Not including the previous two cases, it could also be noticed that across all panels the symmetric MGARCH model usually provides a lower hedging potential than its asymmetric equivalent. The bunker-gasoil pairs once more translate into the most optimal hedge ratios while the combination of spot position with RBOB performs the worst closely behind WTI. The other futures contracts, that is, ULSD and Brent, vary across both sulphur alternatives and four ports.

Let us now comment on the out-of-sample hedging effectiveness presented in Tables 6.13. Variances are again round up to five decimal points for the purpose of reporting, which is why variance terms sometimes entirely coincide in terms of static and dynamic models, but reduction may differ to some degree. The results are in a sense presaged by the in-sample evidence. Naïve approach massively increases variance and could be regarded as a rather unreliable technique with the variance reduction taking values from -98.59% to 3.72%, which is an unusual feature as our data do not support 1-to-1 approach in all but one example, and that is, RIFO-gasoil pair. We move on to the other types of hedge. Closer inspection of Rotterdam bunkers in *Panels A* and B do not favour either of the HSFOs or LSFOs. The best hedging effectiveness can be achieved using RMGO spot with gasoil reaching the reduction in risk by as much as 23.08 %. Singapore spot contracts as displayed in *Panels C* and *D* do not appear to give any preferential treatment concerning low and heavy sulphur alternatives reducing the variance of the portfolio from 1.95% up to only 8.27%, which is in stark contrast to the in-sample illustration. Correspondingly, Table 6.14 gives hedging effectiveness for Fujairah and Houston ports. *Panels A* and *B* narrowly supports the choice of HSFOs in terms of MVHR as little as 3.40% obtained from the ADCC model. Contrary to common practice, dynamic models slightly increase variance for the pair of FMGO-ULSD and that could be attributed to excessively volatile hedge ratios. Hedging performance reported in *Panels C* and *D* suggest using HFSOs instead of LSFOs to reduce exposure from price fluctuations. While the HEI ranges from 2.18% to 5.50% for the former case, the latter yields the values from 0.28% to 5.28%. In summary, these clear patterns imply that spot contracts under research work well with gasoil futures as their hedge in terms of risk reduction is the highest.

A high number of rolling windows tested allows us to make deductive reasoning possible and formulate generalizations where necessary because the out-of-sample evidence in such a way guarantees high statistical power. When compared to the in-sample evidence, the out-of-sample rolling window procedure provides a lower shield against the variability in prices of petroleum-refined products. The occasional dominance of dynamic models cannot be understood anyhow, but that OLS appears to be more consistent and powerful than their non-static equivalents to a certain extent. Therein stands the result indicating that constant hedge ratios might be more significant for companies' decisions.

Table 6.12: Out-of-sample hedge ratios

Panel A: RIFO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel E: FIFO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.30409	0.32747	0.19427	0.34442	0.53361		OLS	0.14299	0.18055	0.14394	0.18882	0.25331
	DCC	0.26305	0.31271	0.17179	0.30394	0.44276		DCC	0.13031	0.16793	0.08756	0.15813	0.22509
	ADCC	0.28112	0.31651	0.16863	0.31054	0.45606		ADCC	0.13163	0.16933	0.08799	0.15964	0.23125
Panel B: RMGO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel F: FMGO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.20769	0.26371	0.13333	0.25034	0.48421		OLS	0.01838	0.01653	0.04716	0.02596	0.06754
	DCC	0.20817	0.27610	0.12800	0.24500	0.47653		DCC	0.03917	0.03794	0.01971	0.03901	0.05823
	ADCC	0.22109	0.28045	0.13476	0.25325	0.47743		ADCC	0.03979	0.03835	0.02191	0.03941	0.06271
Panel C: SIFO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel G: HIFO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.18111	0.22226	0.13179	0.23723	0.31804		OLS	0.21485	0.22409	0.14626	0.25758	0.34471
	DCC	0.13979	0.20189	0.08476	0.16659	0.29000		DCC	0.18172	0.22613	0.14825	0.21994	0.32076
	ADCC	0.15962	0.21053	0.09556	0.18358	0.29579		ADCC	0.20688	0.24959	0.16282	0.24633	0.33765
Panel D: SMGO		WTI	ULSD	RBOB	Brent	Gasoil	*Panel H: HMGO*		WTI	ULSD	RBOB	Brent	Gasoil
	Naïve	1	1	1	1	1		Naïve	1	1	1	1	1
	OLS	0.12017	0.15065	0.09882	0.14416	0.26469		OLS	0.07919	0.11215	0.05734	0.10152	0.21314
	DCC	0.10127	0.12961	0.05505	0.10756	0.22313		DCC	0.19310	0.12608	0.06249	0.10402	0.19310
	ADCC	0.11406	0.14089	0.06246	0.11929	0.22532		ADCC	0.21123	0.13941	0.07600	0.11327	0.21103

Note: Panels report out-of-sample hedge ratios between respective bunkers and corresponding futures contracts. Non-constant hedge ratios are computed as the mean of hedge ratios within a given sample.
Source: Author's computations.

Table 6.13: Out-of-sample hedging effectiveness – Rotterdam, Singapore

		WTI		ULSD		RBOB		Brent		Gasoil	
		Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction
Panel A: RIFO											
	Unhedged	0.00062		0.00062		0.00062		0.00062		0.00062	
	Naïve	0.00085	-38.15%	0.00075	-21.56%	0.00108	-75.61%	0.00077	-25.03%	0.00059	3.72%
	OLS	0.00056	9.01%	0.00057	6.71%	0.00059	4.67%	0.00056	**9.54**%	0.00057	6.67%
	DCC	0.00056	8.84%	0.00057	6.69%	0.00059	4.60%	0.00056	9.41%	0.00056	8.76%
	ADCC	0.00056	8.95%	0.00057	6.69%	0.00059	4.59%	0.00056	9.45%	0.00056	8.54%
Panel B: RMGO											
	Unhedged	0.00036		0.00036		0.00036		0.00036		0.00036	
	Naïve	0.00071	-98.59%	0.00054	-51.16%	0.00061	-76.58%	0.00060	-69.58%	0.00037	-3.01%
	OLS	0.00033	7.27%	0.00033	7.53%	0.00034	3.81%	0.00032	8.73%	0.00027	22.48%
	DCC	0.00033	7.27%	0.00033	7.51%	0.00034	3.80%	0.00032	8.73%	0.00027	22.47%
	ADCC	0.00033	7.24%	0.00033	7.50%	0.00034	3.81%	0.00032	8.73%	0.00026	***23.08***%
Panel C: SIFO											
	Unhedged	0.00059		0.00059		0.00059		0.00059		0.00059	
	Naïve	0.00097	-64.51%	0.00081	-36.07%	0.00115	-94.61%	0.00085	-43.92%	0.00072	-20.93%
	OLS	0.00057	3.32%	0.00057	3.21%	0.00058	2.23%	0.00056	4.70%	0.00058	**5.82**%
	DCC	0.00057	3.14%	0.00057	3.18%	0.00058	1.95%	0.00057	4.29%	0.00056	5.77%
	ADCC	0.00057	3.27%	0.00057	3.20%	0.00058	2.06%	0.00057	4.46%	0.00056	5.79%
Panel D: SMGO											
	Unhedged	0.00031		0.00031		0.00031		0.00031		0.00031	
	Naïve	0.00056	-88.31%	0.00058	-87.73%	0.00058	-88.36%	0.00059	-95.44%	0.00047	-52.33%
	OLS	0.00030	2.82%	0.00029	2.85%	0.00030	2.43%	0.00029	3.62%	0.00028	7.79%
	DCC	0.00030	2.75%	0.00030	2.79%	0.00031	1.95%	0.00029	3.14%	0.00028	7.59%
	ADCC	0.00029	2.82%	0.00029	2.84%	0.00030	2.01%	0.00029	3.26%	0.00028	**8.27**%

Note: Panels are structured according to spot contracts specifications. Variance is computed using Equations 4.34-4.37. Reduction represents hedging effectiveness in percentage terms according to Equation 4.33. Superior hedging performance for individual bunkers is reported in bold. On top of that, the single best hedging strategy is displayed in italics.
Source: Author's computations.

Table 6.14: Out-of-sample hedging effectiveness – Fujairah, Houston

		WTI		ULSD		RBOB		Brent		Gasoil	
		Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction	Variance	Reduction
Panel A: FIFO											
	Unhedged	0.00065		0.00065		0.00065		0.00065		0.00065	
	Naïve	0.00107	-66.18%	0.00089	-38.01%	0.00119	-83.83%	0.00095	-47.66%	0.00081	-25.99%
	OLS	0.00063	1.89%	0.00063	1.94%	0.00063	2.43%	0.00062	2.73%	0.00062	3.38%
	DCC	0.00063	1.88%	0.00063	1.93%	0.00063	2.06%	0.00062	2.66%	0.00062	3.33%
	ADCC	0.00063	1.88%	0.00063	1.93%	0.00063	2.07%	0.00062	2.67%	0.00062	**3.40**%
Panel B: FMGO											
	Unhedged	0.00012		0.00012		0.00012		0.00012		0.00012	
	Naïve	0.00019	-64.57%	0.00019	-59.26%	0.00021	-73.57%	0.00023	-88.17%	0.00021	-77.96%
	OLS	0.00012	0.17%	0.00012	0.87%	0.00011	**1.39**%	0.00012	0.27%	0.00011	1.28%
	DCC	0.00012	-0.05%	0.00012	-0.06%	0.00012	0.92%	0.00012	0.21%	0.00011	1.26%
	ADCC	0.00012	-0.05%	0.00012	-0.06%	0.00012	0.99%	0.00012	0.20%	0.00011	1.27%
Panel C: HIFO											
	Unhedged	0.00074		0.00074		0.00074		0.00074		0.00074	
	Naïve	0.00108	-46.30%	0.00095	-28.76%	0.00128	-72.96%	0.00098	-32.53%	0.00084	-14.36%
	OLS	0.00071	3.75%	0.00072	2.62%	0.00072	2.21%	0.00070	4.45%	0.00069	5.49%
	DCC	0.00071	3.66%	0.00072	2.62%	0.00072	2.21%	0.00070	4.36%	0.00069	5.46%
	ADCC	0.00071	3.74%	0.00072	2.58%	0.00072	2.18%	0.00070	4.44%	0.00069	***5.50***%
Panel D: HMGO											
	Unhedged	0.00029		0.00029		0.00029		0.00029		0.00029	
	Naïve	0.00054	-83.17%	0.00049	-67.34%	0.00047	-59.08%	0.00038	-32.31%	0.00049	-66.54%
	OLS	0.00029	1.28%	0.00028	1.65%	0.00029	0.85%	0.00028	1.74%	0.00027	5.27%
	DCC	0.00028	1.37%	0.00028	1.62%	0.00029	0.85%	0.00028	1.74%	0.00027	5.22%
	ADCC	0.00027	2.27%	0.00028	1.55%	0.00029	0.76%	0.00029	0.28%	0.00027	**5.28**%

Note: Panels are structured according to spot contracts specifications. Variance is computed using Equations 4.34-4.37. Reduction represents hedging effectiveness in percentage terms according to Equation 4.33. Superior hedging performance for individual bunkers is reported in bold. On top of that, the single best hedging strategy is displayed in italics.
Source: Author's computations.

6.4 To hedge or not to hedge

Having uncovered the dynamics of correlations as well as means to minimize various exposure in spot-futures markets, we may proceed with the likely implications for policymakers equally as participants in the shipping and marine industries. The underlying commodity ideally should move in the same direction and close together.

As some useful results have emerged and the clear ranking performance of different models in the out-of-sample is almost identical to the in-sample, we will focus on the former hedging effectiveness. The largest OHR values are around 0.50 from OLS and ADCC model, suggesting that to minimize risk for short hedgers, one dollar bought in the spot is sold by about 50 cents of futures. The absolute winner appears to be OLS reducing the variance of a portfolio by roughly 23% at most. The result is consistent with Ji and Fan (2011) as the type of asset and sample choice play an important role. It is questionable whether such figure is appealing to companies or whether other methods of risk protection could be more attractive in the bunker market. In general, variance reduction ranges from 0.18% up to that 23.08% for the positive outcome, which is mostly deemed as ineffective (Maghyereh et al., 2017). Also of interest is that the MVHR measures only the second moment of the returns distribution but some investors prefer to know the tail risk of the hedged portfolio (Mirović et al., 2017).

The best performing contract is gasoil that reduces the variance of portfolio by nearly 30% at most for the in-sample hedge contrasting 43% of Alizadeh et al. (2004). This feature could be observed in every port. A clear preference for cross-hedges can be drawn from both correlations and hedging effectiveness analysis. From the most to the least efficient derivative financial contract, the order is as follows: gasoil, Brent and WTI with ULSD and RBOB alternating. It can favourably compare to Wang and Wu (2012) who assert that conventional or reformulated gasoline prices could be regarded as the most volatile commodities. As opposed to Lim and Turner (2016) and Pan et al. (2014), our results do not confirm that ULSD is usually the best cross hedge in energy markets. Moreover, our conclusions do not meet with Chang et al.' (2006) proposition that WTI specification displays greater efficacy in risk protection than Brent crude oil. However, it is well established in the literature that there are limited hedging opportunities owing to the absence of a proper derivatives market that would sufficiently offset the risk of price movement in the spot market (Maghyereh et al., 2017; or Basher and Sadorsky, 2016).

Further attention is centered on different bunkers. Asset allocation based on the in-sample hedging effectiveness is not uniform across global ports as we can see that LSFOs should be hedged in Rotterdam and Singapore in contrast to HSFOs for Fujairah and Houston. The out-of-sample case leans towards using HSFOs with the exception of Rotterdam. Local conditions in demand influence the degree of hedging effectiveness, but not chosen derivatives. The inferior performance of both Houston and Fujairah contracts is in line with the findings of Alizadeh et al. (2004) who advocate that regional markets with small exchanged volumes are affected only marginally via futures when tracking the spot contracts. There is no clarification as to why there is an apparent regularity in that ICE contracts are more convenient than NYMEX energy futures. Surely, they are more contemporaneously correlated as we can see in figures of dynamic correlations in the Appendix, reaching the degree of correlations as high as 40% with some peaks of more than 80% consistently during the times of distress. We also contend that the sensitivity of correlations or hedging ratios to the asymmetry phenomenon is *not* supported by our data. In this regard, our conclusions differ from those found in the papers of Baruník et al. (2015), Efimova and Serletis (2014) and Radchenko (2005).

Following Pan et al. (2014), we advocate that more sophisticated models might not generate better hedging outcomes due to larger estimation errors as a consequence of more parameters in the multivariate models. Besides that, it is not unlikely to think that dynamic hedge ratios are far too volatile to ascertain the highest hedging effectiveness across the whole range of commodities within the marine and shipping industry. If we combine these two premises and couple them with a far too variable market, we could arrive at the conclusion that using the standard OLS regression yields more effective results. In consequence, *Hypothesis* 3 is disproved. Carrying out daily rebalancing associated with MGARCH models is infeasible in practice because that would require excessive operational costs. We do not want to completely find faults with dynamic correlations for investment purposes. What is possibly better is to use these models for tracking variations in time where their usefulness is irreplaceable. Their advantage is described in greater detail in Subsection 6.1 of this chapter. Not unexpectedly, we find evidence that unconditional correlations tally with the range derived from the mean of conditional correlations and their standard deviation. While the PPMMCC shows higher correlations for LSFOs in case of Rotterdam and Singapore, it is not supported by Fujairah and Houston ports. This is an oversimplification since the Appendix figures give a more complete measure of such relationships.

6.5 HSFO versus LSFO

In this subsection, we attempt to connect all the previous points to outline an environmentally friendly set up. Not limiting our attention to surveying the returns' dynamics despite its paramount influence, we also want to consider risk minimizing goals and how they could be targeted with respect to future evolution of bunker price mechanisms.

We present a specific shipping fuel overhaul to find the most convincing argument for either switching to LSFO alternative or whether to remain compliant with heavy sulphur ones. Obviously, comparing the investment potential of these scenarios, which hedging surely is, may be too shallow because charterers and shipping companies do want to consume such assets immediately. Having said that, we believe that a certain example of asset allocation might be helpful in recognizing distinct attributes of IFOs and MGOs. Fundamentally, it is practical to at least know these basics. The most convincing argument used by the followers of this view is the fact that balancing supply and demand of bunker prices is difficult insofar as we presumably do not have a good account of bunker market interconnectedness.

Within the scope of this thesis, we cannot hope to cover all the possible implications of the question. However, by disentangling variance and correlations components, we identify that LSFOs tend to correlate with futures weakly or at best moderately. To understand this point more generally, our plots depict that while HSFOs-futures pairwise correlations fluctuate more heavily, they are considered to be stronger tools in various investment decisions than MGOs. It is also convenient to assume that bunkers should not be hedged with RBOB even in Houston due to its variability. The use of ULSD in blending may be understood as only a temporary solution. Moreover, different local conditions prevent from the uncomplicated pricing of mainly low sulphur options (Birkett, 2019; and Stefanakos and Schinas, 2014). Hedge ratios across ports seem to strengthen these conclusions. It is wise to proffer an opinion that switching to lower sulphur may not be the most ideal way to handle the sulphur cap in the long run.

Our findings are also in accord with Panasiuk and Turkina (2015) and Chu-Van et al. (2020) who strongly argue that cost effectiveness of HSFOs and scrubbers is wide enough to overcome the primary benefits of MGOs as stable sources of information. On another note, to finance scrubbers requires relying on a healthy differential between the price of HSFO and compliant fuel so that the upfront investment could be deemed sensible. It has been expected that LSFOs would likely to be priced much closer to ULSD than in recent years, abandoning a tight connection with HSFOs prices. This is further discussed in Birkett (2019) who purports that the pricing mechanism of heavy oils will probably be a much stronger function of sulphur content than it has in the past. Figures A.3-A.10 in the Appendix give interesting findings in this sense since MGOs with ULSD do not appear to correlate strongly even in recent times. According to this, we underpin our suggestion to use heavy sulphur oils and to routinely rely on stronger and more positive correlations.

It is widely reported in the recent studies on economically efficient candidates for the IMO 2020 (such as Chu-Van et al., 2019) that residues of crude oil distillation with higher sulphur content are far more attractive investment assets. This is unsurprising given how cost-benefit analysis is usually structured. Nevertheless, the figures of dynamic conditional correlations, hedge ratios along with hedging effectiveness indicate that the bunker industry should cross hedge gasoil. *Hypothesis* 4 is thus partially true since crude oil futures contracts do not provide the best hedging performance while IFOs along with scrubbers appear to be a safer bet concerning low sulphur fuel regulations. Abadie et al. (2017) believe that Rotterdam bunkers strongly co-move with crude oil. Since we ensure a clearer difference between sulphur fuel oils, our study attests to the fact that European futures contracts are more reliable in terms of variance reduction and investment objectives, putting Brent and WTI in the second and third place in terms of conditional correlations. Based on the OHRs, heavy alternatives are simply better options.

As there are some limitations[2] attached to our optimal hedging strategy, it is necessary to provide their complete run-through as we want to be sure that our results are correctly appreciated. Thereafter, we can wholly state possible avenues for further research. Even though this thesis does not implement a cost-benefit analysis, capital costs and multimillion-dollar up-front expenditures attached to a scrubber (or LNG engines) must be taken into consideration because they have a tremendous impact on companies' decision. In like manner,

2 We should also mention the rolling window technique. In our case, it is a very time-consuming process because one correlation takes roughly one hour of estimation for each model.

capital and operating costs enter into day-to-day affairs. It is convenient to assume that bunker prices are affected by the pricing of petroleum futures contracts but their low correlations give evidence that the bunker market is perhaps too volatile to reflect the changes happening in the derivatives market. It could be interesting to see how the analysis would change in relation to change the hedging frequency and duration of our data. Week horizon seems to be a better choice since the fluctuations are uttered in favour of greater adjustment to unrefined petroleum products. This is the reason why some correlations are almost stagnant. It is especially true for the likes of RIFO-futures contracts, RMGO-ICE contracts and FIFO-NYMEX contracts since the impact of news is practically negligible apart from the 2020 events in a manner of speaking. That may sometimes happen with stock market correlations captured by ADCC-GARCH models (e.g. Paramati et al., 2015), but as far as we know no paper on energy commodities has ever reported it. However, the standard DCC displays normal patterns. Moreover, we must ignore tax policy and transportation costs of bunker prices, which also points to greater volatility of refined product prices. Furthermore, it may be argued that there are more options as to lower sulphur alternatives; nonetheless, our example is sufficiently robust to extra study given four different locations. Finally, the apparent problem with time series research is that we work with historical data and any econometric analysis is thus subject to past information that could hold in the future or not. The best what we could do is to use an out-of-sample forecasting method to 'look ahead' and utilize the asymmetric dynamic conditional correlations so as to define a certain pattern that may only be detected by the appropriate examination of relevant history.

On the basis of the aforementioned restrictions and shortcomings, we believe that our analysis could be extended to other derivatives contracts such as options and FFAs. They may provide a larger risk reduction and could function as a stable instrument that is actually used more than futures contracts in the bunker industry. This could encourage investigation in modelling volatility and correlations of the emerging markets. Deeper insight can also be gained by optimizing portfolios with more than two assets. Lastly, as we are four months in the sulphur regulations, the impact on market players could be analyzed ex-post on micro as well macro levels in the context of future directives, such as the IMO 2030 ambition on the background of the 2030 challenge in carbon neutrality.

Chapter 7

Conclusion

Our thesis extends the earlier empirical literature on the bunker industry (Menachov and Dicer, 2001, and Alizadeh et al., 2004) and tries to connect it with the MGARCH research on asymmetric dynamic conditional correlations by accounting for the intensity among crude oil, its refined products and two classes of bunker fuels, either heavy or low sulphur fuel oils. By considering four major bunkering hubs and the five most traded energy commodities in the world, we also determine prices in their vicinity.

This section is divided into three categories so that we could address each aim of our thesis in its entirety. As we uncover some interesting dynamics among spot-futures correlations, notable findings and recommendations have unfolded. They can be realized by investors, charterers, tanker owners, energy market agents as well as regulatory bodies. The real strength of our paper is in testing different methodological concepts in the relatively unresearched fields of a very non-transparent segment of the energy industry and markets. Only then can we mediate some practical implications with regard to both market stress periods and calm market conditions.

First, our empirical analysis reveals that asymmetric responses to positive and negative innovations are not largely supported in the marine and shipping sectors since only five out of forty pairwise correlations display such features. It appears that it is not the case for Singapore and Fujairah, as those correlations are RMGO-ULSD, RIFO-Brent, RIFO-Gasoil, HMGO-ULSD, and HMGO-Gasoil. On the other hand, the volatility of individual assets is subject to the leverage phenomenon since it is more widespread in our data and conforms to the fact that energy market is governed by significant asymmetric effects and persistence (Wang and Wu, 2012). All futures contracts, Rotterdam bunkers and HMGO exhibit some level of asymmetry in volatility captured by the univariate GARCH model. We remark that rising correlations are associated with recessions and a price decline as indicated by both plots of correlations and prices of spot and futures contracts over time. Prior to the rollout of IMO 2020, there evolved ships' fuel consumption patterns that were later confirmed by the recent losses on commodity markets. As expected, there is heterogeneity in returns of petroleum products. Large and unpredictable swings in fuel prices could be particularly traced in RBOB futures along with bunker fuels. More abundant spikes in some correlations could be attributed to extremely volatile spot contracts; one can thus argue that weekly data may be more illuminating. Contrary to the commonly held perception, IFOs seem to be more volatile than MGOs, which does not necessarily imply that they are inferior for hedging purposes.

Second, the hedging effectiveness analysis by means of the portfolio variance reduction calls for inference. Not producing any desired effect, the 1-to-1 hedge ratio increases portfolio variance, and hence to remain unhedged is a better option in such a case. The VCM structure obtained from the (A)DCC-GARCH models is also used to generate hedge ratios. The HEI ranges from 0.66% to 29.37% for positive, and thus usable, values. What is peculiar is that WTI-bunker pairings usually display lesser hedging potential with ICE futures contracts prevailing. Gasoil is the clear winner among hedging instruments, partially due to its open interest, liquidity, and the fact that bunkers are priced off of it. This is the reason why WTI and Brent may come short in the variance reduction part. By applying the rolling window, we are able to set forward a preposition that static hedge models are sufficiently able to outperform its dynamic equivalents from the perspective of risk management strategy. This leaves the supposedly more efficient method for the correlations and spillovers analysis where the OLS technique ignores changing variability in our data set. What is more, the HEI is usually lower than for the in-sample evidence because the values lie between 0.17% and 23.08%. Hedge ratios are very similar across the OLS and MGARCH models with some occasional superiority of the asymmetric model. For that reason, we might employ the ADCC-GARCH model for asset allocation rather than its symmetric counterpart. This is underpinned by the investigation of correlations since more pronounced and detailed correlations are captured by the former model.

Third, ship-fuel rules influence markets well beyond just bunker fuels. As a contribution to the ongoing debate which path of compliance is reportedly better, we believe that the cost effectiveness of HSFOs and scrubbers is higher than for LSFOs. Local conditions across megahubs surely affect the degree of correlations and hedging effectiveness, but the choice of derivatives is fairly universal. The out-of-sample performance shows that LSFOs are more appealing spot contracts only for Rotterdam. The other instances point to HSFOs, which can be strengthened by the in-sample performance of Fujairah and Houston bunkers. Therefore, there is a tendency to choose IFOs concerning fuel regulations in five out of eight cases. Despite greater volatility, HFSOs also yield higher correlations when combined with the energy derivatives. Taking into account capital costs and the lay-ups when ships cannot operate, we still have confidence in heavy sulphur alternatives.

We also discuss the obtained results and compare them with the previous research. It can be stated that the most novel findings arise from conducting the dynamic conditional correlations analysis as mentioned above. There are some caveats that must be accounted for because we restrict our study mainly on the econometric theory and modelling so the cost-benefit analysis is largely disregarded. The shortcomings of our research are thus related to possible future extensions in respect of the emerging markets and the upcoming regulations in the following decade.

In summary, risk associated with market uncertainty, various regulations, and other global phenomena cannot be reduced to zero point. There are myriad large factors, let alone small factors, that influence every issue mentioned in each chapter of our thesis. In the upshot, we wish to conclude where we started off – with the Engle's Nobel lecture delivered on December 8, 2003:

"There are some risks we choose to take because the benefits from taking them exceed the possible costs."

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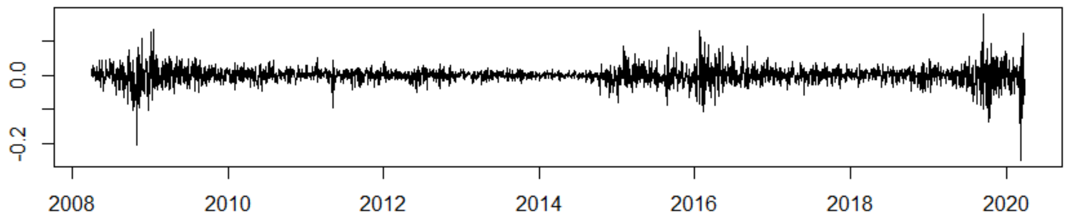
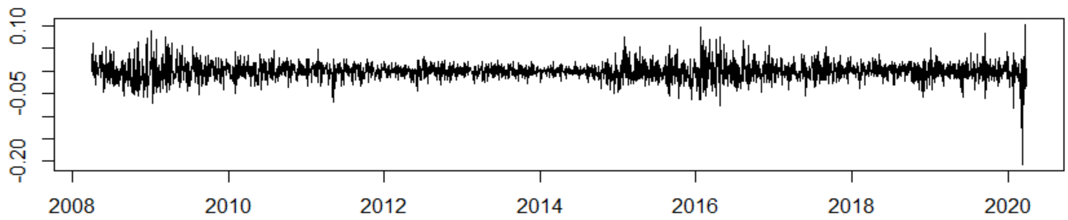
Appendix

Figure A.1: Return series of spot contracts

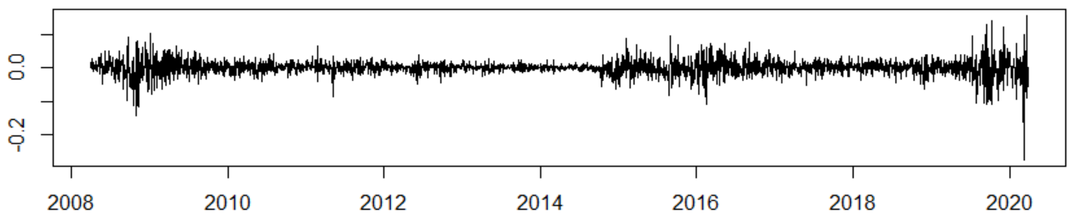
(a) RIFO



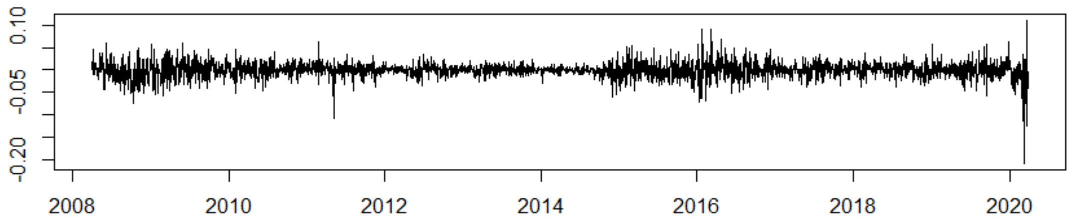
(b) RMGO



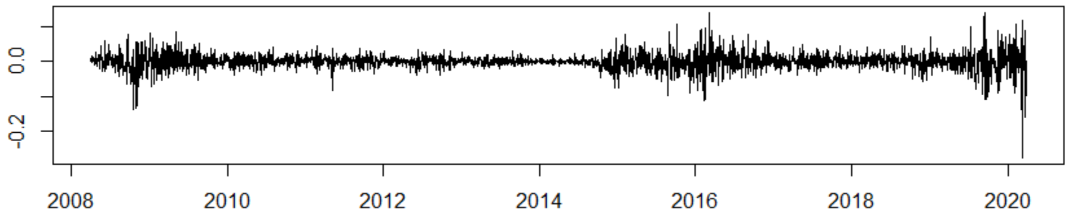
(c) SIFO



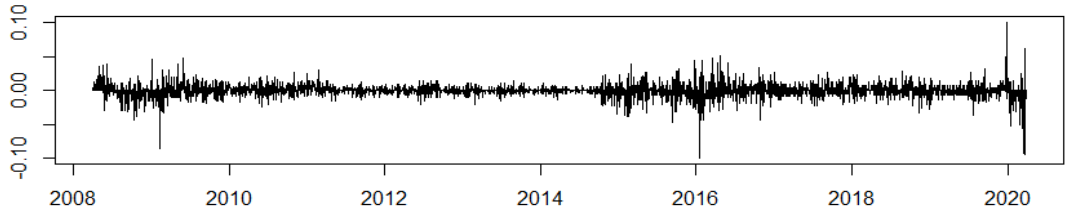
(d) SMGO



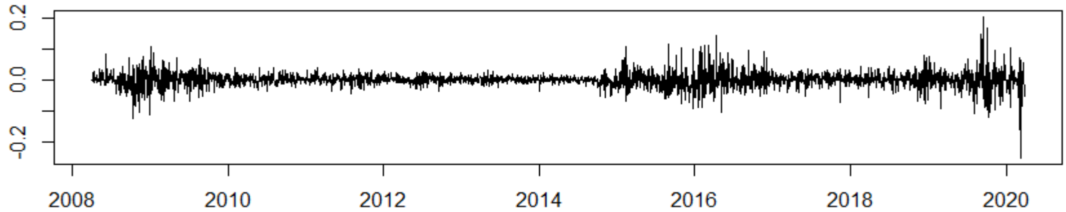
(e) FIFO



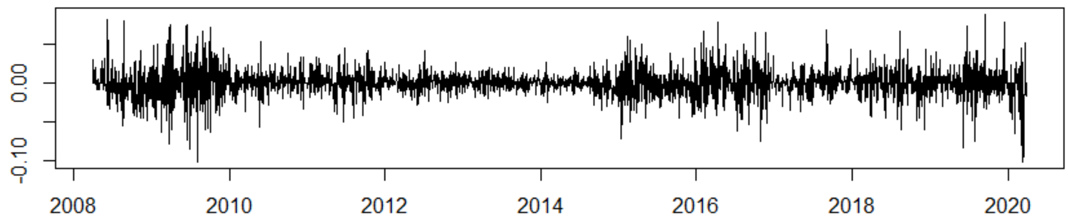
(f) FMGO



(g) HIFO



(h) HMGO



Source: Author's computations.

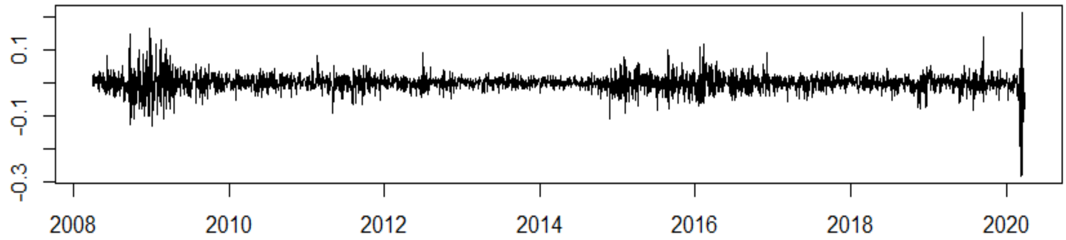
Table A.1: Critical values of unit root and stationarity tests

	ADF			KPSS		
	10%	5%	1%	10%	5%	1%
critical values	-1.62	-1.95	-2.58	0.347	0.463	0.739

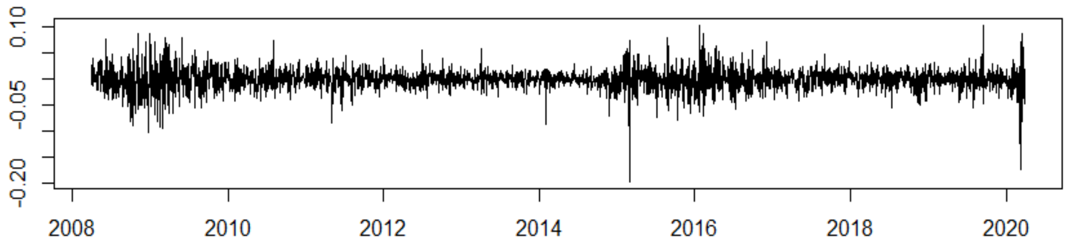
Source: `http://home.cerge-ei.cz/petrz/GDN/crit_values_ADF_KPSS_Perron.pdf`; CERGE-EI (2008).

Figure A.2: Return series of futures contracts

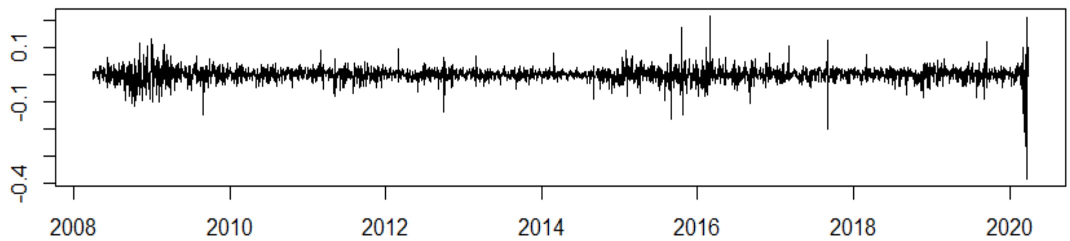
(a) WTI



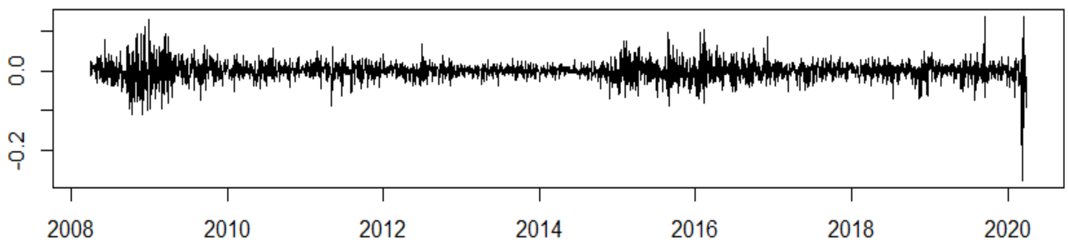
(b) ULSD



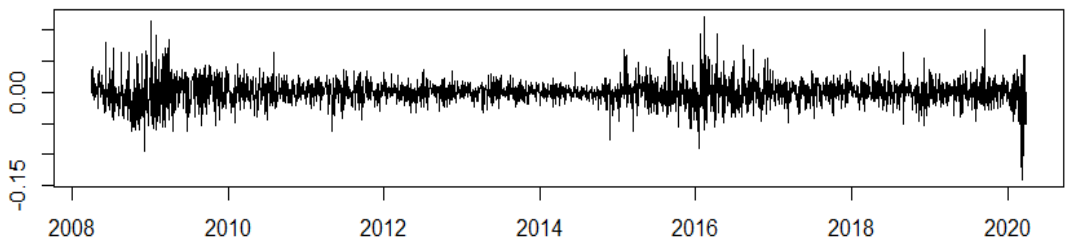
(c) RBOB



(d) Brent



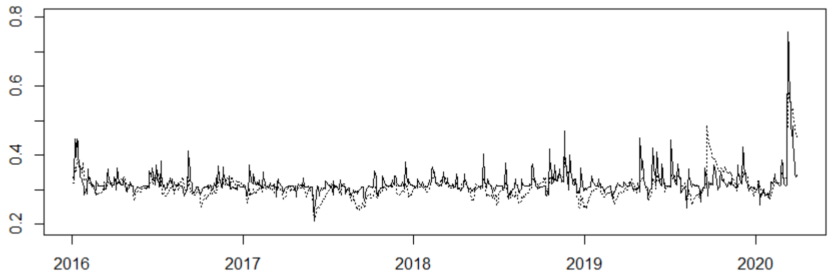
(e) Gasoil



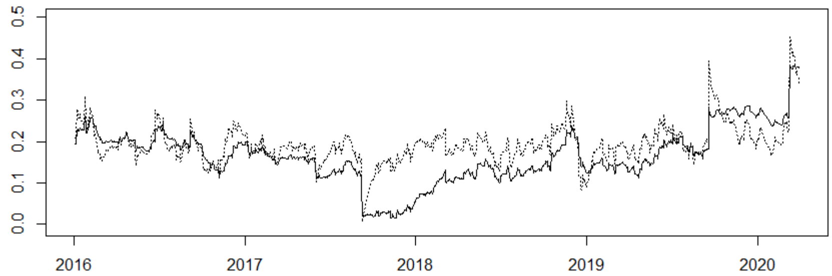
Source: Author's computations.

Figure A.3: Dynamic conditional correlations between RIFO and futures contracts

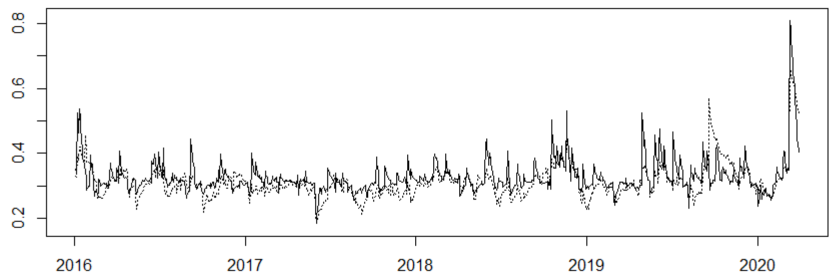
(a) WTI



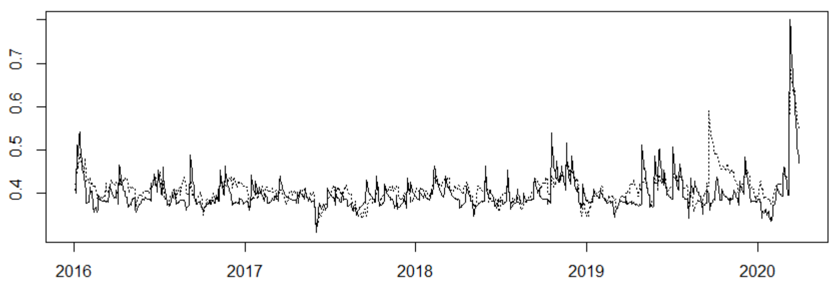
(b) RBOB



(c) Brent



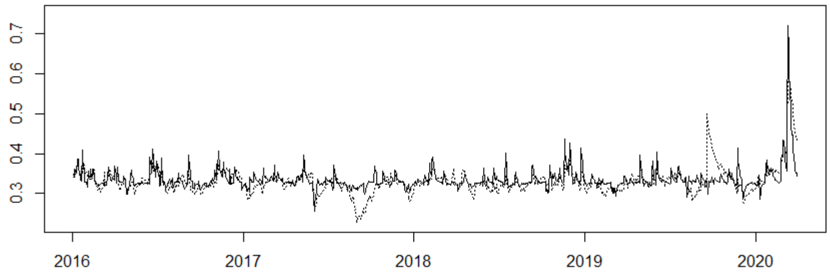
(d) Gasoil



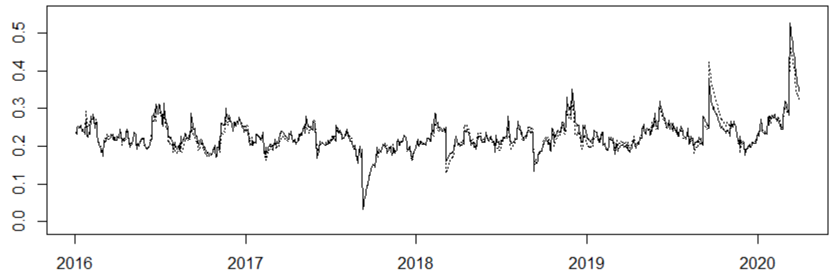
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.4: Dynamic conditional correlations between RMGO and futures contracts

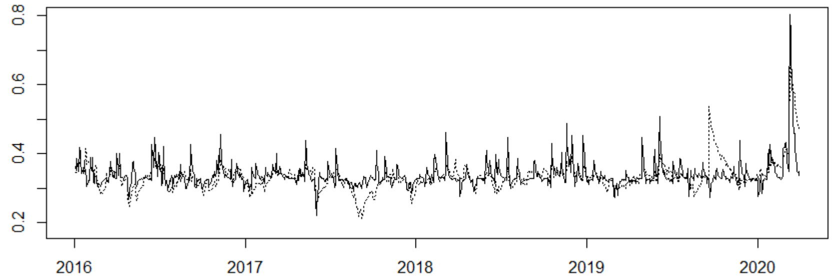
(a) WTI



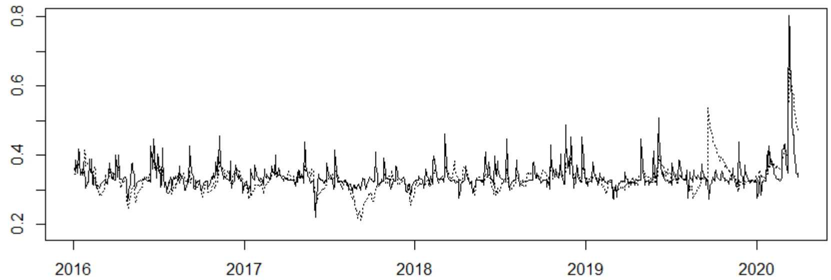
(b) RBOB



(c) Brent



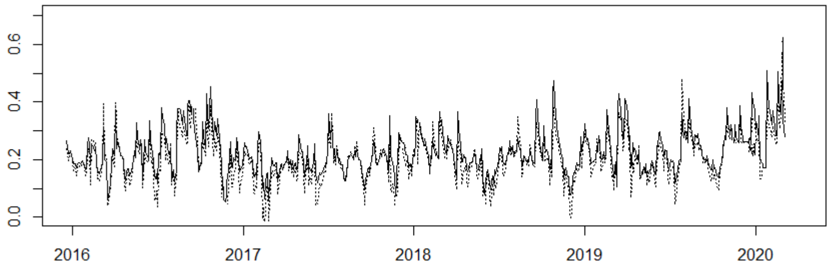
(d) Gasoil



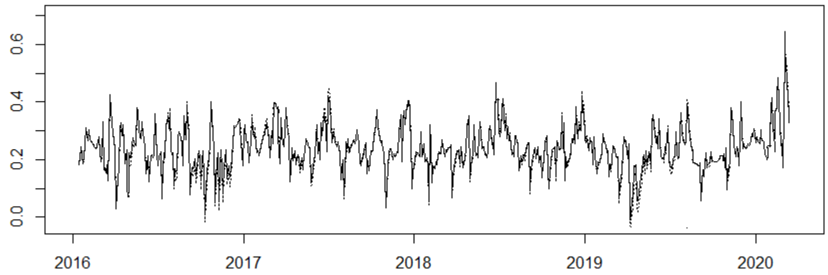
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.5: Dynamic conditional correlations between SIFO and futures contracts

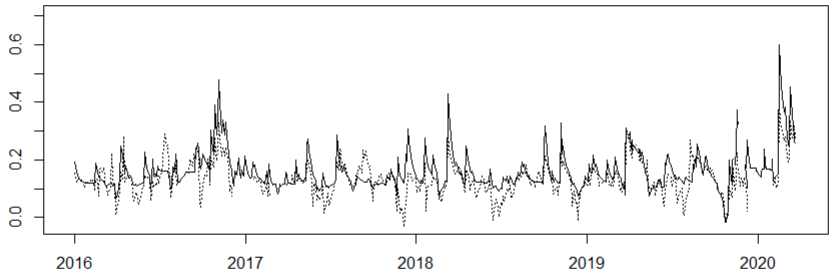
(a) WTI



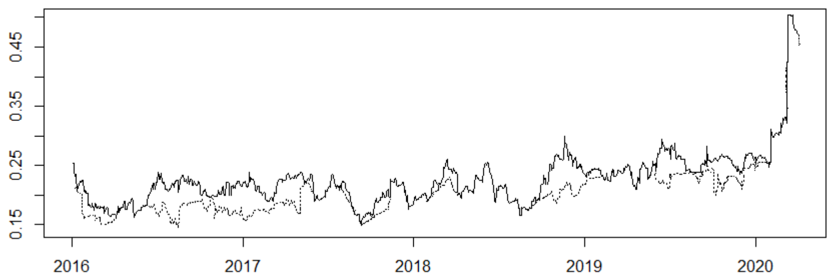
(b) ULSD



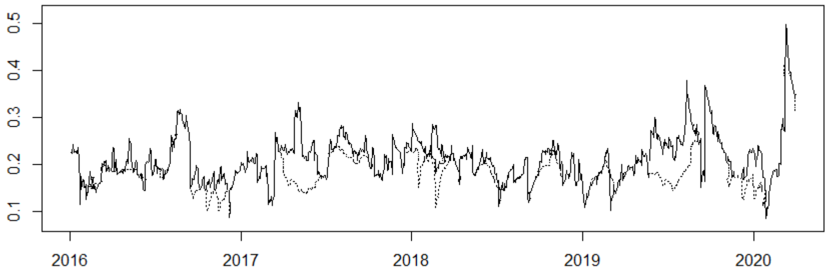
(c) RBOB



(d) Brent



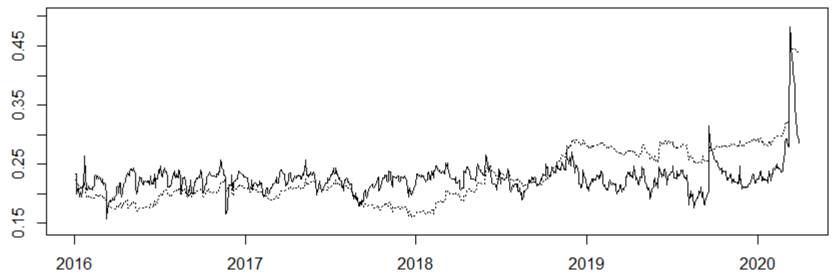
(e) Gasoil



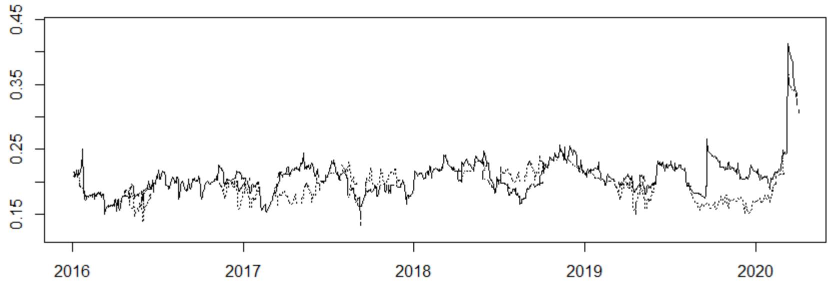
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.6: Dynamic conditional correlations between SMGO and futures contracts

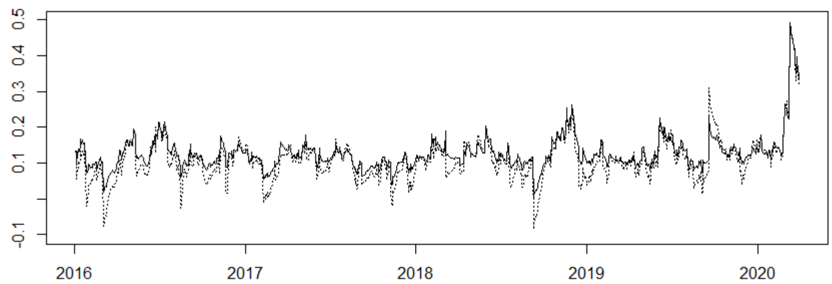
(a) WTI



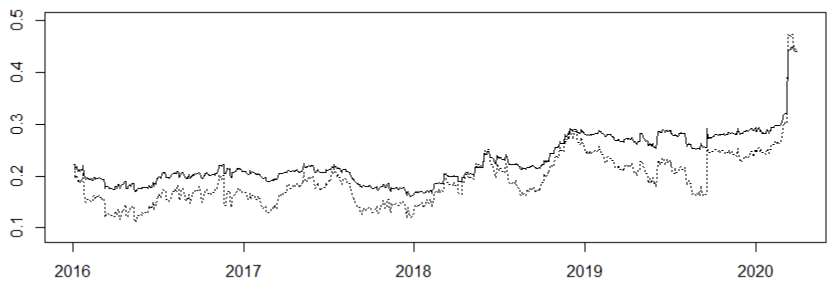
(b) ULSD



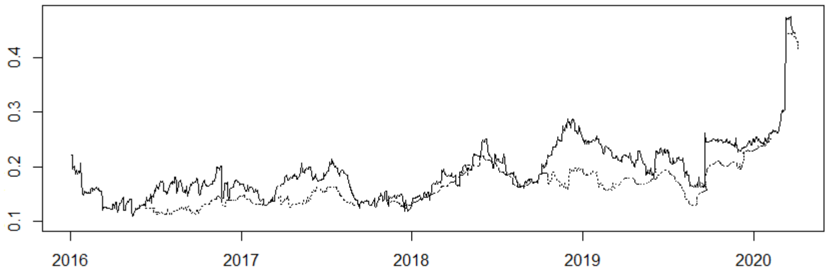
(c) RBOB



(d) Brent



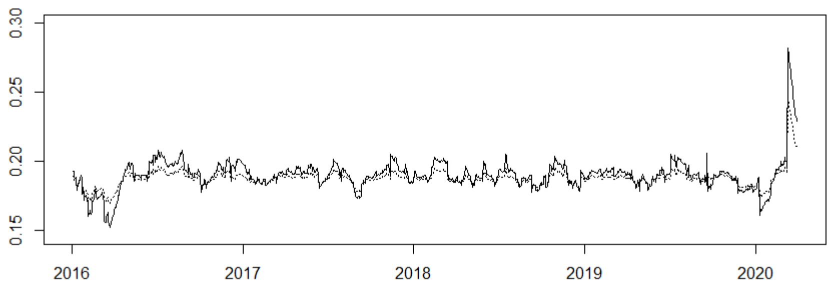
(e) Gasoil



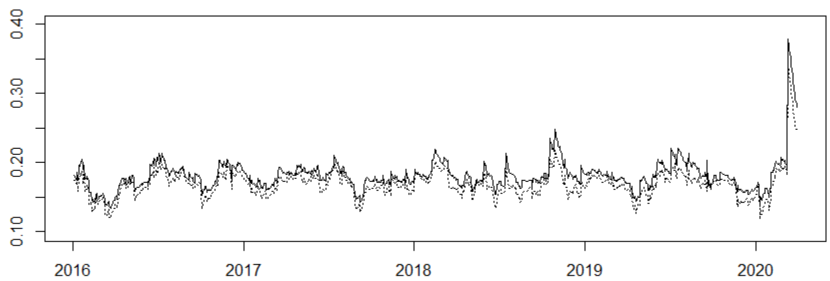
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.7: Dynamic conditional correlations between FIFO and futures contracts

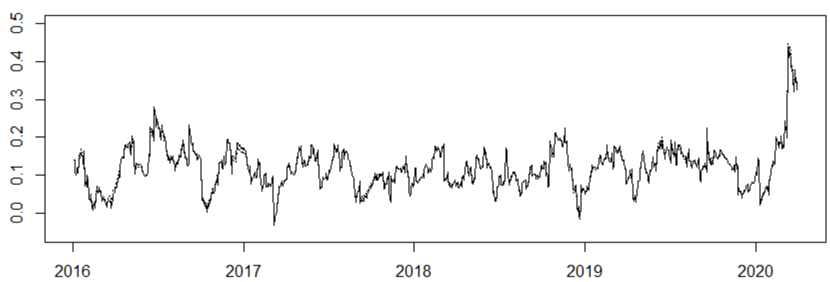
(a) WTI



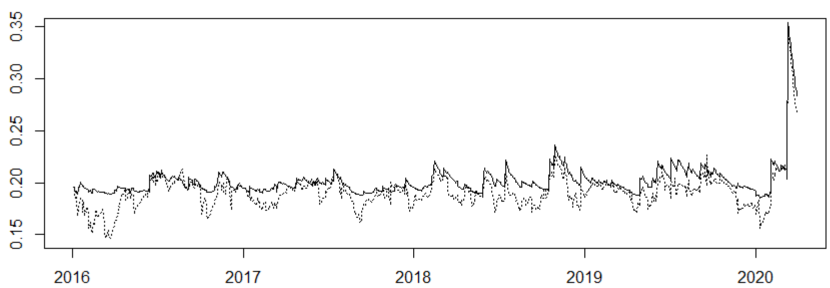
(b) ULSD



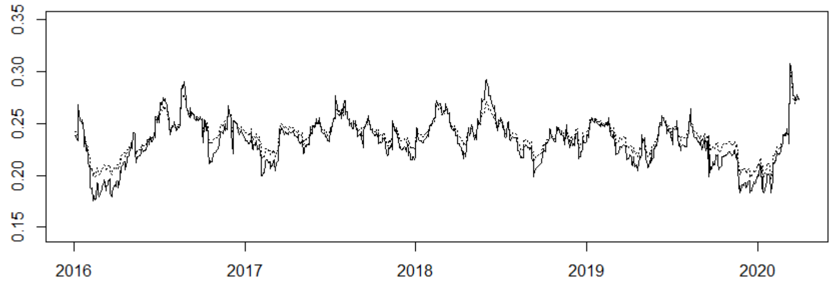
(c) RBOB



(d) Brent



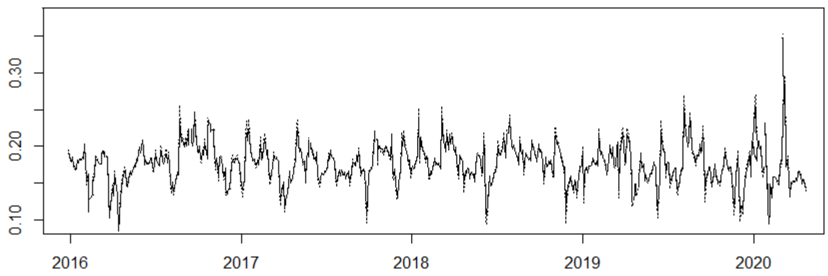
(e) Gasoil



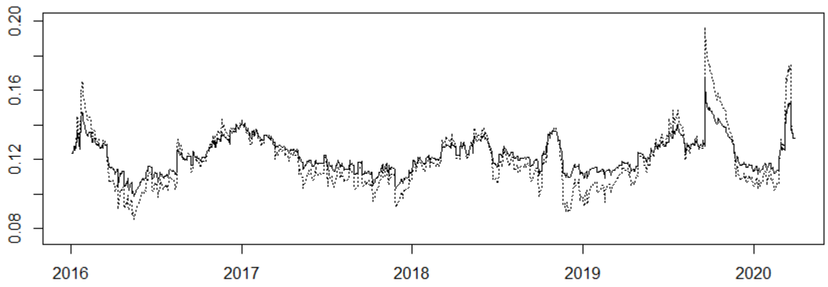
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.8: Dynamic conditional correlations between FMGO and futures contracts

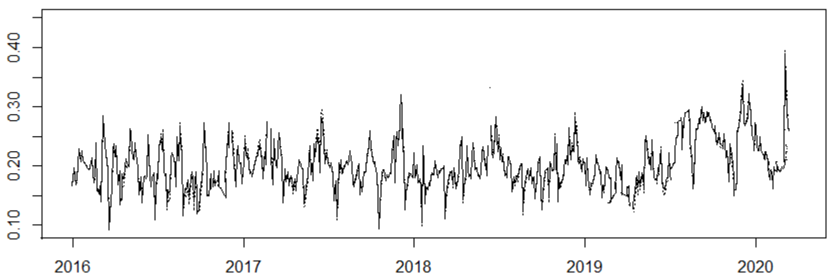
(a) WTI



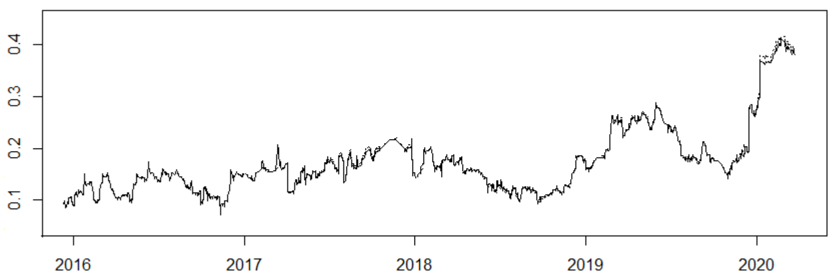
(b) ULSD



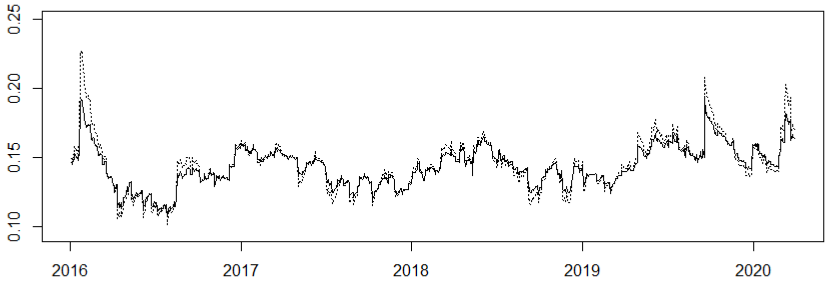
(c) RBOB



(d) Brent



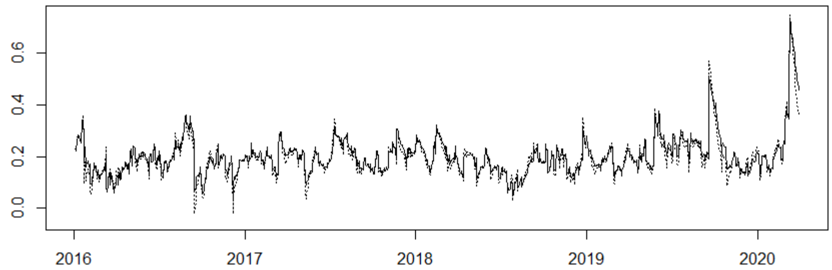
(e) Gasoil



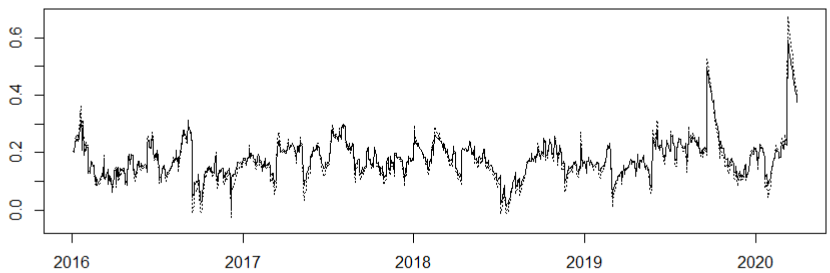
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.9: Dynamic conditional correlations between HIFO and futures contracts

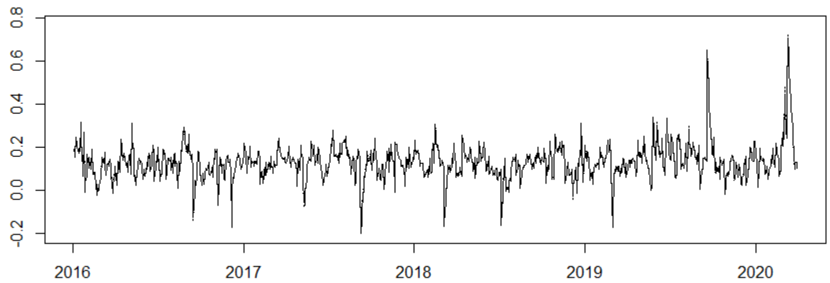
(a) WTI



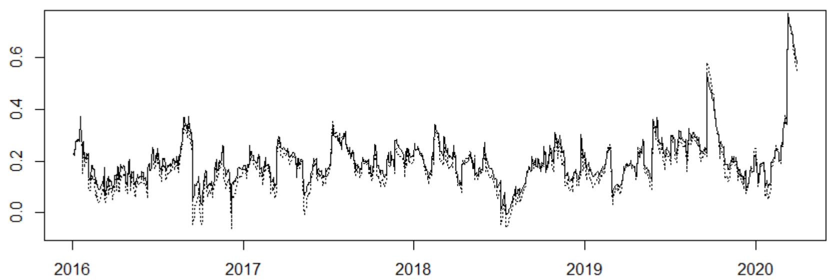
(b) ULSD



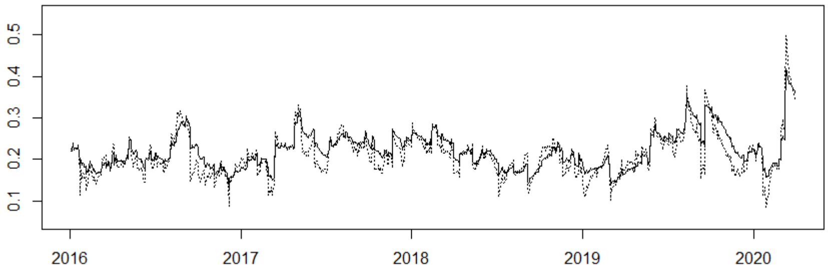
(c) RBOB



(d) Brent



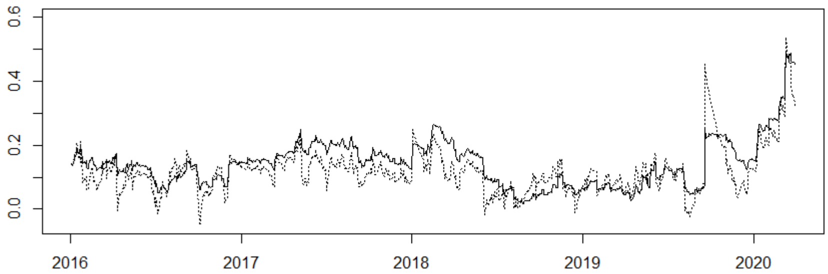
(e) Gasoil



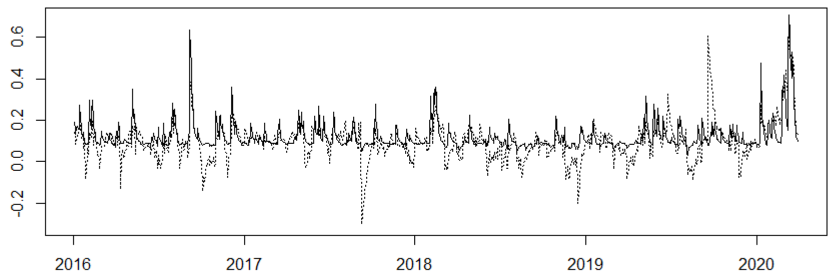
Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Figure A.10: Dynamic conditional correlations between HMGO and futures contracts

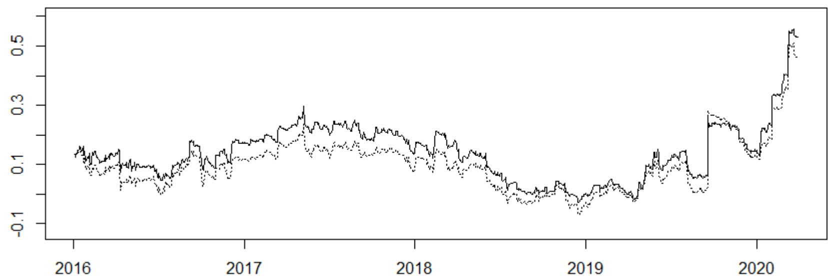
(a) ULSD



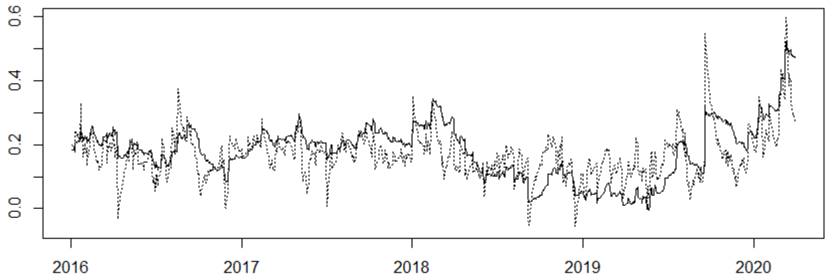
(b) RBOB



(c) Brent



(d) Gasoil



Note: Dotted lines represent correlations based on the DCC model, solid lines designate correlations based on the ADCC model.
Source: Author's computations.

Table A.2: OLS regression with diagnostic checks – Rotterdam, Singapore

Panel A: RIFO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00024 (0.398)	0.00022 (0.361)	0.00022 (0.351)	0.00021 (0.348)	0.00021 (0.362)
	λ	0.16390*** (7.134)	0.24845*** (8.577)	0.18764*** (7.726)	0.23121*** (8.906)	0.44677*** (14.899)
	$\bar{R}^2$	0.038	0.055	0.045	0.059	0.150
	BP	1.612**	0.516**	1.273**	0.379**	2.395**
	BG	0.643***	0.264**	1.299***	1.218**	2.269***
Panel B: RMGO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00005 (0.107)	0.00003 (0.062)	0.00002 (0.054)	0.00002 (0.049)	0.00001 (0.040)
	λ	0.14351*** (7.669)	0.25000*** (10.748)	0.17500*** (8.868)	0.20500*** (9.723)	0.50900*** (22.780)
	$\bar{R}^2$	0.044	0.084	0.059	0.069	0.293
	BP	0.044**	1.138*	0.464**	0.243**	0.594**
	BG	1.327***	2.022***	0.840**	1.151***	2.270***
Panel C: SIFO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00021 (0.362)	0.00019 (0.340)	0.00019 (0.334)	0.00019 (0.331)	0.00018 (0.337)
	λ	0.08972*** (4.214)	0.14769*** (5.481)	0.11169*** (4.960)	0.13381*** (5.530)	0.35657*** (12.732)
	$\bar{R}^2$	0.013	0.023	0.019	0.023	0.114
	BP	0.666**	0.298**	0.052**	0.301**	1.935**
	BG	2.460**	1.971***	2.008***	1.351***	0.996***
Panel D: SMGO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00002 (0.034)	0.00002 (0.004)	0.00001 (0.001)	0.00003 (0.007)	0.00003 (0.017)
	λ	0.08914*** (5.170)	0.14810*** (6.806)	0.09603*** (5.252)	0.13381*** (6.852)	0.32230*** (14.383)
	$\bar{R}^2$	0.020	0.035	0.021	0.035	0.141
	BP	2.185**	1.394**	3.332**	1.102**	1.115**
	BG	1.424***	0.943***	1.686***	1.616***	1.387***

Panels display respective spot returns regressed on the corresponding futures returns. Coefficient λ represents the hedge ratio. Numbers in parentheses are t-statistics based on heteroskedasticity- and autocorrelation-consistent standard errors. $\bar{R}^2$ is the coefficient of determination; in other words, the adjusted R-squared. BP stands for the Breusch-Pagan test with the null hypothesis of homoskedasticity. Analogously, BG denotes the Breusch-Godfrey test with the null hypothesis of no serial correlation. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.

Table A.3: OLS regression with diagnostic checks – Fujairah, Houston

Panel A: FIFO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00021	0.00020	0.00019	0.00019	0.00019
		(0.403)	(0.372)	(0.364)	(0.362)	(0.372)
	λ	0.11706***	0.18944***	0.13965***	0.16192***	0.34709***
		(7.266)	(7.561)	(6.651)	(7.181)	(13.253)
	$\bar{R}^2$	0.091	0.043	0.033	0.039	0.123
	BP	0.017**	0.320**	0.011**	0.002**	0.178**
	BG	1.386***	1.578***	0.997*	1.349***	2.356***
Panel B: FMGO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00004	0.00003	0.00003	0.00003	0.00002
		(0.162)	(0.128)	(0.122)	(0.118)	(0.119)
	λ	0.05960***	0.08298***	0.05970***	0.07350***	0.14540***
		(6.332)	(6.954)	(5.970)	(6.849)	(11.515)
	$\bar{R}^2$	0.031	0.036	0.027	0.035	0.095
	BP	2.893*	1.147**	0.088**	0.153**	0.018**
	BG	0.010***	0.879***	0.031***	0.609***	2.541**
Panel C: HIFO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00020	0.00020	0.00020	0.00020	0.00018
		(0.443)	(0.396)	(0.382)	(0.380)	(0.394)
	λ	0.18907***	0.28439***	0.20382***	0.26637***	0.37897***
		(9.422)	(11.305)	(9.587)	(11.84)	(14.158)
	$\bar{R}^2$	0.066	0.092	0.068	0.100	0.138
	BP	1.129***	1.683**	1.647**	1.337**	0.306**
	BG	1.168***	1.394***	0.804***	2.675***	2.472***
Panel D: HMGO		WTI	ULSD	RBOB	Brent	Gasoil
	μ	0.00008	0.00006	0.00006	0.00006	0.00004
		(0.153)	(0.114)	(0.108)	(0.102)	(0.103)
	λ	0.13080***	0.19060***	0.12250***	0.16880***	0.31540***
		(7.130)	(8.219)	(6.267)	(8.096)	(12.918)
	$\bar{R}^2$	0.038	0.051	0.030	0.049	0.117
	BP	1.016**	0.421**	2.009**	0.091**	1.630**
	BG	86.446***	107.63***	84.622***	98.326***	130.290***

Panels display respective spot returns regressed on the corresponding futures returns. Coefficient λ represents the hedge ratio. Numbers in parentheses are *t*-statistics based on heteroskedasticity- and autocorrelation-consistent standard errors. $\bar{R}^2$ is the coefficient of determination; in other words, the adjusted R-squared. BP stands for the Breusch-Pagan test with the null hypothesis of homoskedasticity. Analogously, BG denotes the Breusch-Godfrey test with the null hypothesis of no serial correlation. The two-side statistical significance at the 1% level is denoted by '***', at the 5% level by '**', and at the 10% level by '*'.
Source: Author's computations.