Modelling spot prices, risk management, and investment strategies for the energy markets

by

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To my parents Dimitris and Giota, my brother Dimitris, and my wife Chrysoula, for all their help and invaluable support.

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Abstract

This thesis addresses the topics of spot price modelling, risk management, and investment applications in the energy markets. Eight of the most important energy markets that trade futures contracts on NYMEX, and one Spot Energy Index (SEI) proposed for the first time in this thesis, are investigated. A new modelling approach is proposed for optimally capturing the behaviour of the energy spot prices, combining a mean-reverting and a spike model that incorporate two different speeds of mean reversion, and time-varying volatility modelled as a GARCH and an EGARCH process. The aforementioned modelling approach is also evaluated in terms of its ability to quantify energy spot price risk by accurately calculating Value-at-Risk (VaR) and Expected Shortfall (ES) measures. A number of commonly used VaR methodologies are evaluated along with various Monte Carlo (MC) simulations based models and a Hybrid Monte Carlo with Historical Simulation (MC-HS) approach, introduced in this thesis for the first time. This thesis also delves into index investment applications for the energy markets that have recently attracted a lot of attention. To that end, the index tracking problem is addressed by applying equity algorithmic trading using two innovative Evolutionary Algorithms (EAs), aiming to replicate the performance of a direct energy commodity investment which is proxied by the constructed spot energy index.

The empirical evidence in this thesis shows that the proposed modelling approach can effectively capture the behaviour of the energy spot prices examined, and that it is the most reasonable, efficient, and consistent approach for calculating the VaR of spot energy prices and the SEI, for both long and short positions. Hence, it can be successfully applied for forecasting, risk management, derivatives pricing, and policy development and monitoring purposes. Finally, it is shown that energy commodities, proxied by the SEI, can have equity-like returns as they can be effectively tracked with stock portfolios selected by the investment methodology proposed in this thesis. The latter investment approach can be used by fund managers to set-up energy Exchange Traded Funds that would track the performance of the SEI, giving them the full flexibility of any investment style, long or short, that equities can provide.

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Chapter 1.
1. Introduction

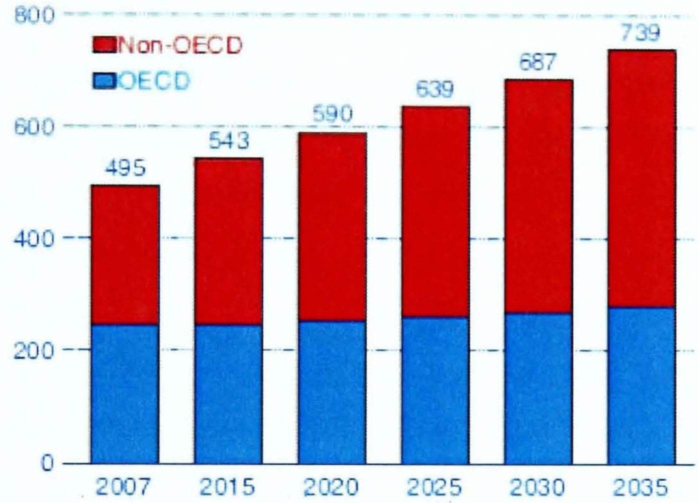
This chapter discusses the most recent developments in the energy markets, along with the theoretical framework and the respective controversies that provide the motivation for this thesis. The most predominant modelling methodologies alongside their risk management applications are discussed. In addition, emphasis is given on the development of commodity indexes as a means of benchmarking, hedging, and investment. Furthermore, the alternative of investing in equities of commodity-related companies and their superior return potential compared to commodity future investment strategies is investigated. Finally, the main empirical findings that are derived from this thesis and its contribution to the body of the existing literature are discussed.

1.1. Introductory notes

In recent years, investors' interest in commodity investments has increased enormously, as a result of the improved risk-adjusted portfolio returns that an allocation to commodities can deliver. Investing in commodities has provided on average equity-like returns, while at the same time has offered negative correlations with traditional asset classes and protection against inflation. A number of papers in the literature explicitly document the inflation hedging properties of commodities (see amongst others Bodie and Rosansky, 1980; Jensen et al., 2000; Gorton and Rouwenhorst, 2006). In addition, a number of macroeconomic factors that occurred simultaneously, prompted the broader investment community to consider commodities. First, an anticipated but sustained increase in consumption from China and countries like Brazil, India, and Russia (the so-called B.R.I.C. countries), is leading into higher future demand for commodities that will be more global in scope. Second, a rebound from historically weak commodity prices, partly due to supply limitations, has also occurred. Many commodities have experienced a prolonged period of declining or flat prices, with some reaching all-time inflation-adjusted lows in the late 1990s, and because of that, during the same time producers and natural resources' venture capitalists avoided investments in production and distribution. Third, the low inventory levels traditionally held by manufacturers because of just-in-time inventory practices, created short-term commodity shortages that led to extremely high prices accompanied by order limits and significant lag times. Fourth, further price pressure to commodities is added by the weak US dollar because, as most commodities are valued in US dollars, more money is needed to purchase them. Fifth, a change in the psychology of investors due to a prolonged commodity up-trend, made them more likely to consider non-traditional investments for their portfolios. Finally, fears for a future inflationary environment is encouraging investors to buy into commodities to take advantage of their potential hedging properties.

According to the BP Statistical Review of World Energy (2010), energy consumption in the OECD countries during 2009 fell faster than GDP, marking the first decline since 1928 and the sharpest decline (in percentage terms) on record. The developing world on the other hand, experienced an energy consumption growth faster than GDP. Looking forward, based on the reference case scenario of the International Energy Outlook (2010) report, world marketed energy consumption, total energy demand in the non-OECD and in the OECD countries is expected to increase by 49, 84, and 14 percent from 2007 to 2035, respectively. The latter two demand percentages pinpoint the increasingly high importance that emerging markets play in the world economy, especially during and after the global economic recession that started in 2007. Most of the growth in energy demand mainly stems again from the non-OECD countries that are also expected to have by far the highest growth in energy consumption compared to the OECD countries (see figure 1-1). Even though most of the developed countries seem to have exited the recession, the recovery has been mostly led by countries such as China and India, with Japan and the European Union member countries being the laggards.

Figure 1-1: World marketed energy consumption 2007-2035, Reference case (in quadrillion Btu).

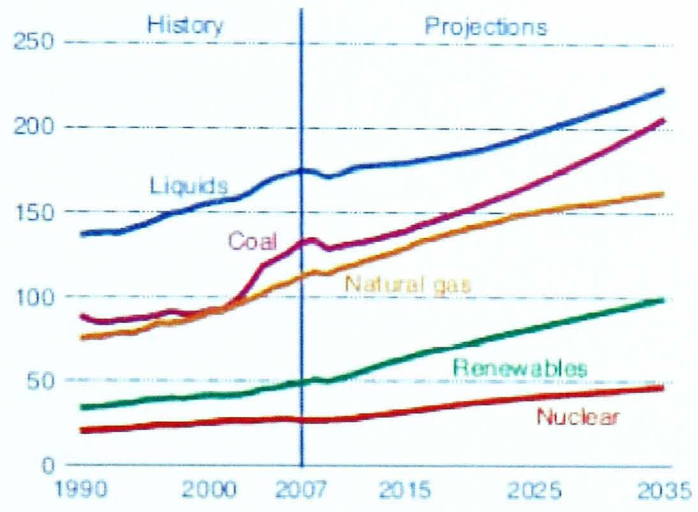


Source: International Energy Outlook, 2010.

In addition, even though consumption of renewable and alternative energy sources is expected to increase in the future, most of the energy consumed worldwide is expected to come from fossil fuels, such as liquid fuels and other petroleum, natural gas and coal (see figure 1-2). Although energy prices collapsed in mid-2008 as a result of the worldwide concerns about the deepening recession, in 2009 prices bounced back and have remained relatively high until now. The latter concerns about sluggish economic growth, in conjunction with certain geopolitical and non-geological[1] factors that limit access to prospective conventional resources, allowed unconventional resources such as oil sands, shale oil, gas-to-liquids, and bio-fuels to become economically competitive.

[1] Non-geological factors include conflicts and terrorist activity, environmental protection actions, labour and material shortages, lack of technological advances, adverse weather conditions etc.

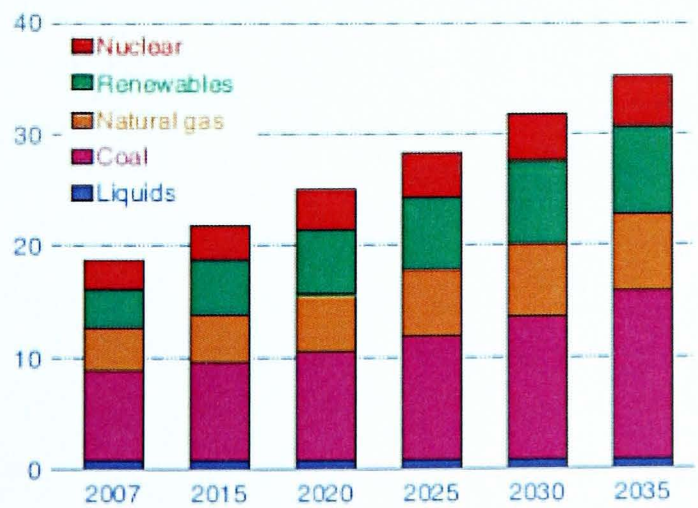
Figure 1-2: World marketed energy use by fuel type 1990-2035, Reference case (in quadrillion Btu).



Source: International Energy Outlook, 2010.

Moreover, increased concerns about the environmental consequences of greenhouse gas emissions, has led to increased interest in alternatives to fossil fuels such as nuclear power and renewable sources, mostly due to higher fossil fuel prices and the receipt of major support by governmental incentives throughout the world (see figure 1-3). However, most renewable generation technologies are not economically competitive with fossil fuels, besides hydropower and wind power that are mainly expected to deliver most of the world's increase in renewable electricity supply in the near future. Typically, renewable electricity generated by sources other than wind and hydro, such as solar, biomass, waste, tidal and wave, is primarily supported by government incentives or policies that fund the construction of renewable generation facilities.

Figure 1-3: World net electricity generation by fuel 2007-2035, Reference case (in trillion kwh).



Source: International Energy Outlook, 2010.

1.2. Theoretical framework and motivation

Energy is what drives modern economic development with the source of the energy supply, in the past two centuries, stemming primarily from hydrocarbons. Due to the previous factors, and in their search for the aforementioned benefits, investors have rapidly increased their allocations to commodities, while at the same time most commodity prices have soared. Nevertheless, even with such a strong momentum, commodity investment strategies have not performed as expected, in many cases underperforming their respective spot indexes. This is because most investors invest in commodity futures and other derivatives, and not in the actual physical commodities or commodity equities. Chada (2010) finds an enormous difference between investing in spot commodities versus investing in commodities futures. He shows that over the past three, five and 10 years, futures investments, proxied by the Dow Jones-UBS Total Return Futures Index, even when including the interest earned on cash collateral, they have trailed spot commodities, proxied by the Dow Jones-UBS Spot Commodity Index, by 5.6 to 11.7 present annually. The author concludes that the differences in the trajectories of performance over time can be mostly attributed to the way that futures-based indexes are constructed. Long-term investors, in order to maintain a continuous exposure to the commodities markets, they need to "roll" the expiring futures contract to a contract with maturity further out in time. This process of rolling forward futures contracts requires active trading, that can have an adverse effect when successive-month contracts trade at prices higher than the current month, leading to the creation of the so-called "negative roll yield".

Investing in physical commodities is generally practical only for precious metals, as for most commodities, and especially for energy markets, investment in the physical product requires many simultaneous transactions that only specialised experts and investors with economies of scale can handle. These complicated and expensive transactions include the purchase, storage, transport, and insurance of the actual commodity, which makes direct investing in spot commodities an impossible investment alternative for a large segment of the investing population. On the other hand, a major disadvantage of commodity futures returns is their burdensome and complicated taxation scheme applied in many countries, making an allocation to commodities suboptimal for taxable portfolios. For example, as Stockton (2007) points out, total returns of derivative based commodity portfolios can be taxed as 60% long-term capital gains and 40% short-term capital gains, whereas the returns of portfolios that hold physical commodities such as gold and silver, can be taxed as profits from collectibles at 28%. Moreover, according to Gordon (2006) another drawback of futures returns is that profits cannot be deferred since the futures contracts need to be marked-to-market at the end of each year.

The recent run-up in oil price and other energy products between 2003 and 2008, and then their subsequent steep collapse within a few months, to many economists appears to be a huge bubble that was meant to burst (Eckaus, 2008). These developments in the price of oil and in other energy markets have been mainly attributed to the positions taken by financial investors on the futures markets, such as pension funds, hedge funds, investment banks etc. These peculiar dynamics of oil, and most of the energy commodities, have transformed them into financial assets, and as such, they are subject to speculative bubbles. As Caballero et al. (2008) argue, the financial collapse of 2007 led investors into a search for an alternative asset class that has diversification properties able to deliver positive returns during a market downturn, and they found it in energy commodities and more specifically in oil. According to them, it is this huge inflow of capital towards energy commodities that created this huge rise in oil prices towards the end of 2008, leading to a speculative bubble that burst only a few months later. As Shleifer and Summers (1990) point out, investors' reactions to common signals or their overreaction to recent news can cause herding behaviour. However, in the case of the oil futures markets, Boyd et al. (2009) and Buyuksahin and Harris (2009) conclude that, during recent years, herding among hedge funds did not destabilise the futures markets because of its countercyclical nature. Moreover, in their study on the performance of various hedge funds and commodity fund investment styles during periods of bullish and bearish stock markets, Edwards and Caglayan (2001) find that commodity funds provide greater downside protection than hedge funds do.

There is also a number of researchers and economists that are more sceptic as to whether the oil price spike was a bubble (see Krugman, 2008; Pirrong, 2008; Smith, 2009), basing their argument on the missing stockpiles of oil. In their opinion, betting in higher future prices for oil and energy products, financial speculators would have increased stockpiling where possible. In the absence of stockpiling in oil and other energy products, their argument states that physical markets could not have been affected by speculation in the futures markets. On the other hand, above ground storage and the creation of stockpiles, in the case of energy markets is a very short-term concern as it is a very expensive solution, when it is even physically applicable; only a very low level of inventories relative to total production is maintained at any given time. Based on the assumption of economic equilibrium, Pierru and Babusiaux (2010) take on the view that an increase in oil prices would reduce demand for oil, resulting in any quantity of the non-consumed supply being stored. Based on this economic viewpoint, any accumulation of stocks, even minimal, would imply that the price of oil is driven by speculation above the level set by market fundamentals. As Parsons (2010) states, during the 2003-2008 period no such stockpiling occurred. Adding to the later finding, Hamilton (2009b) argues that crude oil inventories in 2007 and early 2008 were significantly lower than historical levels. Even when investors expect that the long-term price of energy products will remain high, it makes no economic sense for them to increase their production levels in order to store any excesses in facilities above ground until the time of sale. Thus, the argument that the lack of stockpiling should support the belief that the recent increase in energy prices was not a bubble can no longer be considered valid.

Krugman (2008) and Smith (2009) argue that the price spike of 2007-2008 can be attributed purely to supply and demand factors. As Hamilton (2009a, 2009b) and Kilian (2009) suggest, supply and demand fundamentals can explain the recent price spikes, caused by stagnant production and strong demand for energy products, which in turn led the short-term elasticity of oil to historically low levels. During the past decade, there has been a big swift in market fundamentals, mostly caused by strong economic growth in the developing countries like China, India, and Brazil, which was not only rapid but at the same times persistent for a long period of time, increasing demand for oil and other energy products. At the same time, supply of oil and other energy products has been very slow in adapting to the demand, because of falling supply rates from mature and depleted oil fields, and because of the big time lag between new investments in oil and energy production and actual delivery of the projects. Thus, the aforementioned imbalance between supply and demand can be attributed as the major factor for the sharp price increase.

Nevertheless, as sound as the previous argument appears to be, the recent transformation of the paper energy markets due to increased investor appetite for alternative asset classes, which can be very influential, is overlooked. According to Parsons (2010), financial innovations made it possible for paper oil and energy contracts to be considered as a pure financial asset, thus making it very similar to equities in this regard, opening the way for the development of a speculative bubble. Based on data reported by the Bank for International

Settlements (BIS, 2009) the notional amounts outstanding and the gross market values of commodity derivative contracts traded over-the-counter, including energy contracts, in mid-2008 were $13 trillion and $2.2 trillion, respectively. A big portion of these funds has been directed into commodities' index funds or index trading, since investors can buy into a commodity index much as they would buy into a mutual fund.

The latest run-up and subsequent steep fall in energy prices is also connected to investors' expectations related to the anticipated USD appreciation and the rising inflation, caused by falling interest rates and the huge liquidity injections into the banking system. In a pursuit of speculating on the emerging markets' economic growth, to overcome the sub-prime financial crisis that originated in the US in 2007, and to hedge against the two aforementioned risks, investors bought huge amounts of energy futures contracts, all denominated in USD. In the same lines, Bermudez and Cristo (2008) show a large negative correlation between oil prices and the USD/ EUR exchange rate, standing at -93% for the 2007-2008 period. As most energy prices (all of those traded in NYMEX) are quoted in USD, consumers react to any price changes expressed in their local currency, so it is to their benefit to push for a depreciation of the USD against their local currency. This process, in effect, brings additional demand into the market pushing USD denominated prices further up. However, as the sub-prime crisis later on proved to be global, affecting most of the developed economies, investors were facing the risk of deflation in their home countries and a strengthening of the USD. Amidst the worldwide recession and the troubled economies of the euro zone, all US denominated assets were now being considered by investors as the safest choice. Under these new economic parameters, in August 2008, investors sold their positions en masse, resulting in a steep fall in all energy prices.

1.2.1. Energy price modelling and risk management

A sound understanding of the stochastic dynamics of energy prices is a prerequisite for making an investment into energy commodities. As it is widely stated in the literature, the evolution of energy prices is determined by a host of factors on both the supply and the demand side. Some of the factors affecting the former are global population growth, changing global trade patterns, changing technologies and many others. As for the latter, technological advances for drilling in previously inaccessible locations (e.g. deep sea drilling), and the realization of new resource discoveries are only some of the influential factors. In addition, there are plenty of political factors across the globe affecting both the demand and the supply side. Because of the aforementioned specific characteristics of energy prices, the risk management ideas and models developed for the financial markets are not directly applicable to the energy complex.

There are a growing number of new and innovative structure products and investment vehicles for energy commodities that come to market, in a continuous search for profits, stemming from price level increases. For example, this increasing demand by investors to gain simple access to direct commodities exposure has led to the development of exchange-traded commodities (ETCs) in July, 2005[2]; over the past five years there are more than 140 ETCs listed in London alone. These ETCs offer long, short, forward, and leveraged exposure to more than 23 individual commodities and 11 indexes (Bienkowski, 2010). The development of the ETCs opened up commodities markets to ordinary investors, who can now choose which individual commodity or index they would like to invest in, without the requirement of daily management, as it is the case with individual futures cotracts. However, ETCs are still subject to roll yield in the same manner as an investment in a futures contract, which still makes them different than investing in the spot markets. Depending on the state of the futures curve, whether it is in backwardation or contango, ETCs can outperform or underperform spot market returns.

In today's fast moving and at the same time risk loaded trading environments, managing risk effectively is a critical success factor for any trading business. The liberalization and the subsequent innovation in the energy markets across the world, though it comes with plenty of opportunities, it brings along a number of risks for its participants. A key for succeeding in the liberalized energy markets is the ability to manage effectively these new risks that have developed the need for risk transferring products, such as energy futures, options and swaps. Risk is embedded in any form of investment, and as in the financial markets there cannot be any excess returns without risk. To deliver excess returns to shareholders, risk must be taken, with some losses being unavoidable. However, this is also the main purpose of risk management, to monitor these risks and confine the losses within pre-specified levels.

The lack of good risk management practices can often turn out to be very costly for the participants in the energy markets. It can lead to negative profit and loss accounts, increased

[2] ETF Securities (ETFS) in collaboration with Shell Trading created the world's first ETC in July, 2005.

cost of capital, liquidity crises and increased volatility. Also, besides being subject to traditional financial risks such as price-, credit-, settlement-, liquidity-, and operational-risk, the energy markets are also subject to energy specific risks. These include, volume-, location basis-, cross commodity price-, or cash/futures basis-, physical-, regulatory-, and political-risk. The latter three risks, though also present in traditional financial markets, are not as important as in the energy markets. With increased management calls for a simple risk measurement that would be easy to interpret, a single number as represented by Value-at-Risk, has recently dominated as the most suitable risk management tool.

The potential gains from effective enterprise management of risk can be large, affecting positively the profit and loss, reducing cost of capital and business volatility, while at the same time enhancing working capital management. Moreover, what makes risk management really important for commodity investors is the significant downside volatility that is inherent in individual commodities. Even during a bullish market, short-term supply/demand disruptions can occasionally cause dramatic downturns. Commodities prices are steeply cyclical and investors should expect to withstand price declines of large magnitude, as prices are able to reach all-time highs and subsequently new lows within a short period of time. A stellar example of this commodities' price behaviour is the all-time high price for spot crude oil that reached $145 per barrel in July 2008, and then fell to $38 per barrel by December of the same year, bouncing back to a level of $70-80 per barrel shortly after.

1.2.2. Commodity indexes and their investment applications

Historically, commodities were considered to be inappropriate investments because of their perceived higher risk compared to traditional investments. However this situation has changed with the poor performance of traditional assets and the wider availability of commodity data and commodity related indexes. This led to commodities emerging from obscurity to the front pages of both alternative and mainstream investment publications, with assets pilling into commodity-related indexes and investment products. This large flow of money into commodity indexes can be attributed to the diversification properties of commodities in the context of portfolio management. Georgiev (2001) finds that when adding a commodity component to a diversified portfolio of assets, as proxied by the GSCI, the Dow Jones-UBS Commodity Index, or the S&P Commodity Index, enhanced risk-adjusted performance can be achieved, along with inflation hedging properties especially from the energy and metal sub-sectors. Buyuksahin et al. (2010), after studying the relation between commodities and traditional financial investments from the perspective of a passive investor, as represented by the returns on investable commodity and equity indexes, conclude that commodities can still retain their role as a diversification tool for investors' portfolios, due to the lack of high return co-movement across equities and commodities. Nijman and Swinkels (2003) find that by adding commodities, using the GSCI as a proxy, investors can reduce the volatility of the funding ratio of retirement saving schemes by more than 30 percent. In the same lines, Huberman (1995), Froot (1995), and Satyanarayan and Varangis (1996) show that commodities in general help reduce the unconditional risk in investors' portfolios, while Erb and Harvey (2006), Gorton and Rouwenhorst (2006), and Miffre and Rallis (2007) praise the strategic and tactical values of commodity investments.

What is more with commodity index trading, is that investors do not necessarily have to take a view of whether the price is too high or too low, but instead buy the market as a whole and expect any return from any future price appreciation (passive investment). However, Akey (2005) finds that commodities as an asset class can also provide many opportunities for skilful active managers to find alpha opportunities, by actively managing commodity futures and other derivatives, and/or commodities-related securities. While there is no official source reporting the total amount invested in commodity indexes, press estimates put the number for mid-2008 at $400 billion, of which approximately $130 billion invested in crude oil alone (Parsons, 2010). Buyuksahin and Harris (2009) find that traditional speculators, proxied by non-commercial traders as well as commodity swap dealers[3], tend to exhibit trend following behaviour over their full sample and all its sub-periods. Nevertheless, the authors fail to find any causality from the speculators' positions to prices. This increased popularity of energy index trading has lead to a plethora of hedge funds and investment banks creating their own customised index version. These indexes have different components, weights and other rules, which unavoidably make them different from one another in terms of both historical and expected performance.

For example, the initial commodity indexes were constructed by including the most liquid contracts and therefore limited themselves to the shortest maturity contracts. This structure

[3] According to the CFTC report, non-commercial traders include floor brokers, traders, and managed money traders (hedge funds). Also, commercial swap dealers who use the futures markets to hedge their OTC positions are considered to be speculators because they lack direct exposure to the underlying commodity market. On the other hand, commercial traders are all those dealers, producers, manufacturers, and other entities that are directly involved with the actual commodities involved.

has benefited those indexes for most of their existence, since the shortest maturity contracts exhibited the highest returns, because the oil and the fuels futures curves were most of the time in backwardation. Thus, although spot returns may have been negative at times, the realized returns on the short-term factor more than compensated for that loss. However, this trend has lately changed, with most of the energy markets, including oil, being in contango, thus leading to the generation of negative returns on the short-term factor (Lautier, 2005). When the price of oil began to continually rise in 2003, the spot price returns became the most important and consistent contributor to portfolio returns, making investments in energy futures indexes worthwhile, even though the oil futures curve turned to a state of deep contango since the end of 2004, leading to loses on the short term factor. What has been observed lately is an upward move of the oil futures curve at all maturities, resulting to returns on a futures portfolio to originate solely from the rising spot price. Because of these changing dynamics in the energy futures markets, liquidity started to move into the longer maturity contracts, mostly because of the trades of financial investors.

As Parsons (2010) argues, even with these changes in the dynamics of the energy markets, energy commodities are still included in investors' portfolios because of their diversification benefits that are sought to be high. This recent market switch into a deep and persistent contango, however, has significantly compromised the returns on the traditional index portfolio strategies that were heavily skewed towards short maturity contracts, leading to the creation of new indexes that use longer maturity contract to try to capture any gains. This trend following of the state of the energy futures markets, whether they are in backwardation or in contango, can turn out to be very costly for investors that bet on the wrong side of the trend. The proposed investment approach on the other hand eliminates such risks, giving investors more flexibility on their portfolio while at the same time giving them access to the diversification benefits of energy commodities.

To be able to understand the various sources of returns for a long futures program, the concepts of backwardation, contango and roll yield need to be explained first. When a futures contract's price is at a discount (premium) to the spot price of the underlying, the resulting shape of the futures curve is in backwardation (contango). Towards the expiration of a futures contract, when futures markets are in backwardation, it converges or "rolls up" to the spot price. This price difference is the roll yield that investors can capture when commodities futures markets are in backwardation. However, when futures markets are in contango the reverse occurs, with investors making losses from the futures contracts that converge to a lower price. The levels of contango and backwardation can swing drastically both in terms of magnitude and sign, making the term structure of commodity futures contracts the main driver of the return differences among commodity futures.

As Nash (2001) concludes, the roll yield has been a key factor in long commodity futures investments. He shows that oil and its refined products, namely Heating Oil and Gasoline, which have historically been in backwardation, have also offered the highest returns; in contrast to Natural Gas and the agricultural commodities that have been in backwardation for a much shorter period. Erb and Harvey (2006) find that roll returns explain 91% of the long-run cross-sectional variation of commodity futures excess returns over the examined period between December 1982 and May 2004. Till and Eagleeye (2003) point out that it does not serve any economic purpose for an investor to be systematically long non-backwardated futures contracts. According to them, the time to invest in commodities is when inventories are low and their futures curve is in backwardation. Nevertheless, irrespectively of whether the futures curve is in backwardation or contango, in order to keep a long position and roll a contract forward, investors need to actively trade and accept the market prices for both transactions, the liquidation of the current-month contract, and the purchase of the next-month contract. The methodology proposed in this thesis overcomes these types of constraints, since investors can go long the energy commodities, as represented by the spot energy index, independently of whether their futures curves are in backwardation or contango.

Usually, the futures contracts that normally trade in backwardation and have persistent returns are the ones whose underlying commodity is difficult to store (see Kolb, 1996), as is the case for most energy markets examined in this thesis. For these commodities, price appreciations and depreciations play a key role for balancing supply and demand, thus leading to very volatile spot prices. With limited intervention capabilities and slow production responses, energy markets can only respond to short-term supply-demand disruptions via fluctuations in price. As it is difficult to predict the actual demand levels in the future, and because there is usually a long lead-time between deciding on a production increase and the actual production of the commodity, there will always be short-term imbalances between supply and demand, leading to increased price volatility. It is this uncertain forward risk that commodity producers and holders of inventory will have the need to manage via commercial hedging activities. In turn, this increased activity to protect against price decreases puts more downward pressure on commodity futures prices relative to the respective spot prices, resulting in backwardation and thus to positive expected returns for long futures positions. On the contrary, when most of the hedging activity is directed towards protection against price increases, as it happened in 2004, commodity futures markets move to contango.

One of the drawbacks of commodities futures indexes is that they cannot use a market-capitalization weighting scheme. As Black (1976) points out, all futures contracts have zero market capitalization. Ideally, a commodity index should be constructed in an analogous way as in the case of market capitalization stock indexes, i.e. based on the spot price and the reserves of the constituent commodities. However, in contrast to outstanding company stock shares, there is a lack of a proper measure of outstanding reserves for most commodities, resulting in a vast variety of commodities indexing rules used by different providers. As the relationship between backwardation and contango can change from one period to the next, most of the newly created commodity futures indexes have adapted to this phenomenon by adjusting accordingly the weighting scheme and commodity markets selection for their index construction. Because the Goldman Sachs Commodity Index is heavily weighted in crude oil and other futures contracts that were persistently in backwardation, it has experienced large excess returns up to 2004, with their returns being dominated by the roll yield and not by the performance of the actual commodities. In the beginning of 2004 when oil futures turned into a long-lasting state of contango, a situation blamed primarily to excess speculating activities by non-commercial traders, the GSCI excess returns have diminished significantly Buyuksahin et al. (2010). For the rest of 2004 and 2005, excess returns were still positive because the high spot energy returns were able to offset the negative roll returns. However, in 2006 when also spot energy returns turned negative, the index started making losses. Another reason for this recent change in the term structure of oil futures is the large amounts of money flowing into long-only commodity index-linked products. Because demand for second-month contracts is extremely high, in order to keep a long position and roll out of expiring nearby contracts, prices are pushed upwards. This process pushes prices of longer-term contracts above the prices of shorter-term contacts thus affecting the term structure.

1.2.3. Investing in energy commodity equities

Investors that want exposure to spot commodities returns, usually cannot invest in the actual physical products, besides the case of precious metals, and thus seek alternative approaches such as commodity futures and commodity-related equities. However, although commodity futures provide exposure to their respective underlying commodity, as their prices converge to the spot prices on a monthly basis, the link between long-term commodities futures and spot returns is distorted because of the effect it has on the term structure the prevailing backwardation or contango. This effect has been more profound in recent years, since 2004, when contango started prevailing in the energy markets. Commodity equities on the other hand overcome these term structure effects, with relevant research showing a direct and powerful link between the returns of commodity-related equities and their business-related spot commodity prices.

On that note, empirical evidence shows that commodity-market returns are very similar to equity-market returns in terms of magnitude, with equity-like risk (Bodie and Rosansky, 1980; Nash, 2001). The latter finding has recently increased the interest from institutional investors to integrate commodities in their strategic asset allocation and to develop tactical asset allocation strategies. Nijman and Swinkels (2003) test a tactical switching strategy between commodities and stocks and they find that commodity investments can be beneficial to pension funds within a mean-variance framework. Vrugt et al. (2004) use a market timing strategy based on a dynamic multi-factor approach, to forecast monthly commodity returns with a broad range of indicators related to the business cycle, the monetary environment, and the general market sentiment; they find that investors can have superior returns when following their timing asset allocation strategy. It is evident in the literature that up until the early 2000s, commodities and commodity funds perform well during a financial market downturn, while having at the same time a lower correlation to equities (Chow et al., 1999; Edwards and Caglayan, 2001), with energy commodities in specific being consistently negatively correlated to equities. As Till and Eagleeye (2003) conclude, whenever a commodity investment is intended to act as a diversifier for equities it needs to be heavily weighted in energy markets, as it is the energy complex that exhibits a persistent negative correlation to equities.

Investors generally expect that futures indexes are a good proxy for a spot index, because of the high correlation between spot and futures prices. However, this is not entirely true as according to Chada (2010) the Spot Commodity Index used in his paper outpaces the respective Commodity Futures Index by over 5.6 percent per year, even though their correlation is exceeding 99 percent. The correlation measure is not the most important factor for determining which is the best investment alternative, as it only measures the degree to which two variables are likely to move together. It does not provide an adequate measure of the magnitude of the moves, and it also fails to capture the overall trend of the variables' returns over time, especially as those returns compound. A risk-adjusted return measure, as the Information Ratio, is a better and more appropriate performance measure. In addition, long-only futures commodity indexes have little protection against any sudden and large in magnitude downward price spikes, as they have no ability to sell short, they have inherent limitations based on the state of the futures curve (backwardation or contango), and most of them rebalance only once a year. Furthermore, investing in a broad commodity futures index does not reflect any short-term, tactical response to prices, in either the individual constituents or the aggregate commodity market, which can be better captured by investing in a specific segment of the commodities markets, such as the energy sector.

Investing in commodity-related[4] equities is considered to be the best alternative for avoiding some of the inefficiencies of futures returns, as they can play a crucial part in providing exposure to the commodity markets. Some argue that investing in commodities equities is primarily an investment in equities, which does not significantly help to reduce the overall volatility of the portfolio, or improve its risk-adjusted returns. The main concern of the advocates of this argument is that commodities equities are subject to the actions of their company's management in the same manner as for all other equities, which implies that they can destroy shareholder value or break the link between these stocks and the underlying commodities' price movements. Although the aforementioned argument can be valid in some instances, it is generally accepted that commodity equities are not too far removed from the actual commodity, as the value of a commodities company is directly tied to the value of the commodities it produces/ trades. The latter could be justified by the fact that the equity markets of Russia, Brazil and other emerging market countries that their economies depend heavily on commodities, and more specific on energy commodities, and thus have a large

[4] Commodities-related equities are the securities of those companies that are mainly engaged in the production and distribution of commodities and commodities-related products, the so-called pure-play companies.

number of commodity related listed stocks, have witnessed a thriving performance during every recent commodities boom. Moreover, there are plenty of strategies, and their related opportunities, connected to energy production, distribution, and trade finance that are not directly available to futures investors, irrespectively of their approach, passive or active. These opportunities can only be available to investors via the equities markets, as part of the respective companies' valuation.

In general, any increase in the underlying commodity price should result in an increase in the company's earnings, leading into an increase in shareholder value, which in turn is reflected in the share price. Chada (2010) constructs an equally-weighted portfolio of the eight largest energy stocks as of December 2009, and then maps the aggregated changes in revenues and earnings of these stocks with changes in the WTI spot oil price. He concludes that earnings of oil companies tend to generally relate to the spot price of oil, tracking it closely both in up and down markets. Building on the aforementioned, it is believed that tracking the performance of spot energy prices, as proxied by the proposed in this thesis Spot Energy Index (SEI), can be best achieved by optimally selecting portfolios of stocks, and most probably from energy-related stock pools. With such an investment approach, commodity investors can have all the means at their disposal to protect against any sudden downward price movements, that investing in the selected equities portfolios can deliver, and thus can capture all the alpha opportunities that a passive futures index would miss.

1.2.4. Thesis motivation

Considering the above, the motivation for this research mainly stems from the existing controversies in the empirical literature, as to which modelling approach is best for describing the behaviour of energy spot prices, capturing their risk characteristics, and replicating the performance of a benchmark energy index. The most important element of any investment is the implementation process of the portfolio construction and its risk management, in order to be able to achieve a smooth performance during normal times, but also manage to survive during dramatically turbulent times such as the recent global financial crisis.

This thesis proposes an innovative methodology to manage spot price risk of the individual energy commodities and the constructed spot energy index, using VaR. In addition, it explores an innovative way for commodity investors to achieve returns that are comparable to returns available in the spot energy commodities prices, and thus help them get closer to their goal. It also makes commodity investing available to a very broad range of investors, from small retail to large institutional investors. This research carries out a thorough empirical analysis of eight of the most important energy markets that also trade futures contracts on NYMEX, the largest exchange for energy commodities, and also proposes a unique spot energy index, seeking to address the following research questions: First, can a stable benchmark for energy spot prices be constructed so that end-users can be confident that historical performance data is based on a structure that resembles to the composition of the index both at present and in the future, immune from any regular fundamental changes in its structure, thus making the index suitable for institutional investment strategies? Second, what is the best modelling approach for describing the behaviour of the eight spot energy commodities and the spot energy index examined in this thesis? Third, what is the best set of VaR models appropriate to capture the dynamics of the energy prices and the spot energy index, assess their performance while quantifying energy price risk by calculating both VaR and ES measures, as the accurate measurement of energy risk is of outmost importance for the development of the fast-growing energy derivatives and ETFs markets? Finally, how can an effective index tracking strategy be devised, to replicate the unique price/ return behaviour of the spot energy index that allows investors to get closer to the underlying market price trends, using a basket of equities that are liquid and fully investable, and at the same time allow for both long and short strategies that can significantly improve the risk/ return profile of traditional asset portfolios?

1.3. Findings and contribution

Chapter 2 provides a more detailed analysis of the most recent developments in the energy markets in terms of the recent de-regulation applied in most developed countries, the various modelling approaches for pricing and hedging with futures contracts, their price discovery properties, and the fundamental concepts of backwardation and contango. Moreover, the use of indexes as benchmark tools and more recently as trading vehicles is explained. A comprehensive discussion is made on the key differences amongst the most popular commodity indexes in terms of their weighting methodology, which is based on measures such as liquidity or production, arithmetic or geometric calculations, and also in terms of their rules for rolling forward their constituent futures contracts from the next-month to a more distant contract. Finally, the advantages and disadvantages of index-linked Exchange Traded

Funds (ETFs), and their applications on various investment strategies are also meticulously discussed.

A thorough empirical analysis is carried out in Chapter 3 by examining the performance, in terms of explanatory power and goodness of fit, of models that incorporate mean-reversion and spikes in the stochastic behaviour of the underlying asset. Two types of models are considered: a mean reverting model, where prices have the tendency to revert to their long-run mean, and a spike model that incorporates two different speeds of mean reversion to capture the fast mean-reverting behaviour of returns after a jump occurs and the slower mean reversion rate of the diffusive part of the model. These models are also extended to incorporate time-varying volatility in their specification, modelled as a GARCH and an EGARCH process. The performance of each model is assessed on the basis of how well it can capture the trajectorial and distributional properties of the real market process. The energy markets examined are eight of the most important energy markets that also trade futures contracts on NYMEX, Heating Oil, Gasoline, Crude Oil (WTI), Natural Gas, Propane, Electricity (PJM), two Crack Spreads of Heating Oil and Gasoline, respectively, with WTI, and one constructed Spot Energy Index (hereafter named SEI). The SEI is constructed as an un-weighted geometric average of the individual commodity ratios of current prices to the base period prices, set at September 12, 2000, of the first six aforementioned energy markets. In order to compare the aforementioned processes and identify which one describes the data best, 100,000 Monte Carlo simulations are run to replicate the price paths, and then test the goodness of fit of the models using a variety of both quantitative and qualitative tests.

The estimation results from the historical series in Chapter 3 indicate the presence of a "leverage effect" for WTI, Heating Oil, and Heating Oil – WTI crack spread spot log-price returns, whereas for the remaining energy markets and the SEI the presence of an "inverse leverage" effect is found. In addition, results indicate that the inclusion of Poisson jumps to the mean reverting model, in combination with the use of a different speed of mean reversion after a jump occurs for a duration equal to the half-life of the jumps' returns, improves the fit significantly for all energy markets and the SEI. The proposed modelling approach captures very well both the skewness and kurtosis of the actual series. Furthermore, the addition of the EGARCH (1,1) specification for the variance improves significantly the fit of the simulated returns to the actual distributions for most of the energy markets under investigation and the

SEI. This finding is validated by the reported K-S statistics, as well as by comparing visually the simulated to the actual price series. Hence, overall, the proposed modelling approach for energy pricing combined with the findings of chapter 3 is relevant for both policymakers and market participants as it can be applied for forecasting, risk management, derivatives pricing, and policy development and monitoring purposes.

Chapter 4 investigates whether the widely used in the financial world Value-At-Risk (VAR) and Expected Shortfall (ES) methodologies can be successfully applied in the energy sector. VaR is used to identify the maximum potential loss over a chosen period of time, whereas the ES measures the difference between the actual and the expected loss when a VaR violation occurs. A set of VaR models appropriate to capture the dynamics of energy prices and subsequently quantify energy price risk by calculating VaR and ES measures, is proposed. Amongst the competing VaR methodologies evaluated in this chapter, besides the commonly used benchmark models, a MC simulation approach and a Hybrid MC with Historical Simulation approach, both assuming various processes for the underlying spot prices, are also being employed. The model specifications for the MC simulations and the hybrid approach are the common MR and MRJD, modified to allow for GARCH and EGARCH volatility, and for different speeds of mean reversion after a jump is identified. All VaR models are empirically tested on the eight spot energy commodities and the spot energy index. A two-stage evaluation and selection process is applied, combining statistical and economic measures, to choose amongst the competing VaR models. Finally, both long and short trading positions are considered as it is extremely important for energy traders and risk managers to be able to capture efficiently the characteristics of both tails of the distributions.

The results from Chapter 4 show that, at the 1% significance level, for all commodities and the SEI there is at least one model that passes all three statistical tests with the ARCH type, the MC simulation, and the Hybrid MC-HS models prevailing more. For the entire fuels complex, including the WTI, HO, Gasoline, and the crack spreads with WTI, and for both long and short positions, the MC simulations methodology under the MRJD specifications, followed by the Hybrid MC-HS models, pass all three statistical criteria from the first evaluation stage, and at the same time deliver the lowest LF at the second evaluation stage. The only exceptions are the WTI and the CS-HO-WTI just for the long trading positions, with the ARCH-type methodologies delivering the lowest LFs, respectively. Therefore, it is concluded that the two former approaches are the most reasonable, efficient, and consistent candidates for calculating the VaR of energy prices, for both long and short positions.

Chapter 5 aims to replicate the unique price/ return behaviour of direct energy commodity investment using equities. This goal is accomplished by applying two very efficient in terms of tracking error strategies, the Differential Evolution algorithm (DE) and the Genetic Algorithm (GA), to solve the index tracking problem in the energy markets as represented by the constructed spot energy index. Low tracking error strategies provide several advantages to investors; result in better diversified portfolios, make the long-only constraint of a fund manager less binding, and in general tend to provide higher returns for various equity strategies. More specifically, the performance of the SEI is reproduced by investing in a small basket of stocks picked either from the stocks comprising three well known financial indexes, or from two pools of energy related stocks. In particular, the cases of the US, UK and Brazilian investors are considered who want to invest in the SEI and prefer to access only their local stock markets due to cost savings and/or better knowledge of the respective markets. They represent two developed and one developing stock markets, with the latter having its unique energy significance in the global scene, with the recent reforms and regulations resulting in increased transparency, stability, sophistication and additional liquidity to its financial markets. This reliability in the Brazilian stock market data is the main reason that it is selected for testing and implementing the proposed investment strategy, as the transparency and liquidity in other stock markets such as that of Russia or other emerging markets that have a large number of commodity related firms can be questionable, sometimes leading to obscure datasets. In addition, while recently many developed countries have sputtered amid weak economic growth, Brazil has continued to thrive, given its rich reserve of natural resources and growing middle class, becoming the fifth-largest economy in the world. The methodology implemented can track the SEI or any other benchmark index by investing in a basket of stocks that each of the evolutionary algorithms will determine. Baskets of maximum 10, 15 and 20 stocks are selected from the following stock pools: Dow Jones Composite Average, FTSE 100, Bovespa Composite, and two unique pools of energy related stocks from the US and the UK stock markets, respectively. The proposed methodology allows investors to be more comfortable with their investment selection since this is drawn out of a stock market that they are more familiar with.

From the results of chapter 5 it is found that energy commodities, as proxied by the SEI, can have equity-like returns, since they can be effectively tracked with stock portfolios selected by the investment methodology followed in this thesis. Overall, during the three-year period examined, which reflects a period before, during and towards the end of the recent global economic recession, an investor would realise positive returns by investing in commodities, as the SEI returns suggest. In fact, when following the index-tracking methodology proposed in this thesis, the selected equity portfolios can actually get investors very close to their goal of replicating spot energy commodities returns, as proxied by the SEI, and as in the case of the energy related stock portfolios and those selected from the Bovespa equity pool, to even outperform the benchmark index. In most cases there seem to be no major differences between the DE and GA selected portfolios, though the GA tends to select portfolios that have a lower tracking error. Both algorithms, in most cases, do not utilise the maximum number of stocks allowed to select, with the DE being more stable in the number of stocks picked between the various cases of the risk-return trade-off; the GA tends to select portfolios quite different in terms of their composition. On average, based on the reported results, portfolios with 15 stocks and with a risk/ return trade-off value of 0.8 is the most desirable combination providing the best results for most tracking portfolios. It is also found that when rebalancing, the additional information available from the latest price data does make a difference on reducing the portfolios' volatility, but the small return deterioration out-weighs the volatility benefits resulting in smaller information ratios. However, between monthly and quarterly rebalancing, the differences are relatively small, but the information ratios are in all cases higher for the monthly rebalanced portfolios, with only one exception for the FTSE selected baskets. Thus, it can be concluded that greater capital efficiency can be achieved with rebalancing than with the buy-and-hold strategy.

Considering the above, the main contributions of this thesis are identified as follows. In contrast with previous work, this thesis expands the choice of available models and the number of energy markets that these models are applied on. Spot prices of the eight most traded energy futures contracts on NYMEX and the constructed spot energy index (SEI) are used, covering the crude oil and all its by-product fuel markets, the soaring - due to their increased environmental importance - natural gas and propane markets, one of the most liquid electricity markets, and an index that represents the overall spot energy sector. The research outcome of this thesis provides a better understanding of how energy markets behave, what is the best modelling approach for each individual spot market and, consequently, the best model for the pricing of the relevant futures and options contracts. Identifying the correct dynamics for the energy prices is of great relevance for hedging, forecasting, and policy making in the energy markets. A further contribution in the literature is the empirical testing of which model can sufficiently capture and describe the dynamics of the two 1-1 crack spreads of crude oil with fuel oil and gasoline that trade futures contracts on NYMEX. From the perspective of a petroleum refiner who operates between the crude oil and the refined products markets, modelling accurately the dynamic behaviour of the two crack spreads and their constituents is of utmost importance, since unexpected changes in the prices of the crude oil or the refined products can significantly narrow the spread and put refiners at enormous risk.

Furthermore, as far as the energy markets are concerned, there has been a recent increase in the relevant empirical literature on testing VaR models and assessing their performance that however, is far from finding any consensus about the appropriate VaR model for energy price risk forecasting. This thesis attempts to close this gap in the existing literature by proposing a set of VaR models appropriate to capture the dynamics of energy prices and subsequently quantify energy price risk by calculating VaR and ES measures. The methodologies employed include standard VaR approaches like the Risk Metrics, GARCH and many other commonly used models, MC simulations, and a hybrid Monte Carlo with Historical Simulations introduced for the first time in this paper. Choosing the most suitable VaR model for each commodity and for the SEI is of outmost importance for all energy market players, traders, hedgers, regulators, and policy-makers as modelling risk is reduced, and thus faulty risk management caused by the selected model's inefficiencies is avoided. In addition, in contrast to most existing studies on VaR modelling that consider only long positions, this paper examines both long and short trading positions, as it is important to know whether the models used can capture efficiently the characteristics of both tails of the distributions.

The accurate calculation of VaR measures in the volatile energy markets, as it is proposed in this thesis, is important for all market players and for the development of the fast-growing energy derivatives and ETFs markets. A significant contribution of this thesis is that spot energy price risk is quantified taking into consideration the occurrence of extreme volatility events, and thus at the same time allowing managers to develop efficient hedging strategies to protect their investments. Moreover, with the proposed VaR model selection process, the modelling risk is minimised, satisfying the strict risk management requirements and control procedures, by reducing the probability of accepting flawed models. In addition, this thesis contributes to the existing literature by quantifying the risk profile of the energy markets, as expressed by the individual spot price series and the SEI, a process vital for many hedge fund managers and alternative investors that recently have been following closely and started expanding their presence in the energy markets. Furthermore, the proposed VaR estimates can be used for setting the margin requirements in the growing energy derivatives market, and more importantly for the energy forwards, futures, and options that are widely used for both hedging and speculation purposes by many industrial players, commodity and investment houses.

In addition, the question whether returns of equity portfolios can be used to replicate the performance of physical energy price returns, aggregated in a portfolio and proxied by a spot index, to the best of our knowledge, has received no attention in the literature. Hence, the contribution of this thesis to the literature is that the index tracking problem in the energy commodities market is addressed and both the DE and GA are applied. What is more, investors are provided with the opportunity to invest in the energy spot markets by choosing stocks from a specific domestic equity market which could appeal more to their investing criteria/ preferences. Furthermore, given the importance of equities in a multi-asset class portfolio, by choosing those stocks that can track the SEI the selected equity portfolios are indirectly insulated from inflation; a key consideration amongst investors and fund managers in an uncertain economic environment. Moreover, this thesis contributes to the existing literature by providing for the first time a broad energy index, incorporating in its calculation electricity market prices, thus reflecting the full spectrum of energy commodities and their by-products besides the commonly used crude oil and its refined fuels. Hence, this thesis sheds more light on the relatively unexplored area of index investing in the energy markets, by investigating three different investment strategies during the three year out-of-sample period, buy-and-hold, quarterly, and monthly rebalancing; accounting for transaction costs where necessary. Thus, with an index tracking methodology that uses baskets of stocks, able to closely follow a spot energy index, investors can achieve greater protection and higher returns especially during a market downturn.

Although the SEI represents the economic importance of the energy group of commodities to the global economy, it primarily serves as a performance benchmark given the limited ability for a direct investment. However, the proposed approach provides investors with an option to track that performance of the constructed spot energy index using a basket of equities that are liquid and fully investable. This allows investors to get closer to the underlying commodity market price trends, something they cannot achieve using a futures price index. Historically, futures index returns have lagged price index returns, with this decoupling of performance being a constant frustration for index investors. Moreover, by tracking the performance of the energy sector with stocks selected by two innovative evolutionary algorithms, promotes a cost effective implementation and true investability. While most mutual funds cannot invest in commodities directly, they can track the performance of the SEI by investing in the stocks selected by the evolutionary algorithms used in this thesis. Thus, the proposed methodology suggests an effective, and at the same time, least expensive way to operate such a fund, giving the full flexibility of any investment style, long or short, that equities can provide. This thesis demonstrates that by following the proposed investment strategy of tracking and trying to "beat" the constructed spot energy index, investors can gain superior results with reduced volatility and improved returns. Finally, the proposed investment strategy adds depth to the capacity of investors' portfolios by giving the flexibility of investing in global securities markets, and at the same time, extends their portfolios' span by including natural resources and tactical strategies that are not available via the futures markets/ indexes.

1.4. Thesis structure

The remainder of this thesis is organised as follows. Chapter 2 gives an overview of the recent trends and regulation of the global energy markets. It gives a brief explanation on the NYMEX exchange and its traded energy futures products, while at the same time sets out to organise and review the existing body of literature on the various modelling and pricing approaches for the energy markets. In addition, the case of the recently booming energy indexes is discussed, and the construction of the proposed geometric average spot energy index is described.

Chapter 3 investigates the behaviour of the eight spot energy prices that trade futures contracts on NYMEX, and the proposed spot energy index. The relative goodness of fit of the different modelling variations proposed is compared using Monte Carlo simulations. Chapter 4 proposes a set of VaR models appropriate to capture the dynamics of the energy prices and subsequently quantify energy price risk by calculating VaR and ES measures. All VaR models are empirically tested on the eight spot energy commodities and the spot energy index, applying a two-stage evaluation and selection process on both long and short trading positions. Chapter 5 addresses the index tracking problem and its investment strategy applications for the energy markets, using two innovative evolutionary algorithms. It presents an investment methodology of reproducing the performance of the proposed spot energy index by investing only in a subset of stocks from the Dow Jones composite average, the FTSE 100 and Bovespa composite indexes, and in two pools including only stocks of the energy sector from the US and the UK respectively.

Finally, Chapter 6 concludes this thesis. In particular, it summarises the main contributions and discusses the findings along with their application in the energy commodities markets. In addition, it considers the limitations of this thesis along with ideas for potential future research.

Chapter 2.
2. Energy markets

In this chapter the most recent developments in the energy markets are discussed. The opening of the energy markets in the developed world, as a result of the recent deregulation, and the complexity of the energy specific contracts, is discussed. In addition, the major energy related commodity exchanges in the world are mentioned, with emphasis given to the available products and the way the NYMEX operates, which is the dominant commodity exchange worldwide. Next, the various modelling approaches are examined, touching upon issues of pricing and hedging with futures contracts, their price discovery properties, and the fundamental concepts of backwardation and contango; all necessary for understanding the major features of the energy markets and their behaviour. Finally, the evolution of the commodity indexes as a benchmarking tool and for describing the market trends is discussed. The focus is mostly on the major energy indexes in existence and their recent applications on investment strategies, such as the creation of Exchange Traded Funds and a number of other similar investment vehicles.

2.1. Introductory market overview and deregulation

Deregulation of the oil and natural gas markets in the US and Canada in the 80's, and in the early 90's of the power industry in the Scandinavian countries, the UK, Australia, and North America, has resulted in increased liquidity, efficiency, and transparency. We need to bear in mind though that the extent of deregulation varied with commodities and locations, as well as the degree of interaction among the components of the value chain that was handled through markets or public utilities. Choosing a side in the debate about competitive markets versus regulation, we believe that the advantages of competition due to the deregulation of the energy markets are beyond doubt and outweigh any disadvantages.

However, the increased competition has led to more volatility in energy prices, exposing the market participants to greater risks. These developments increased the need for risk management in the energy industry, and boosted the use of derivatives as means to control the exposure to volatile energy prices. Although traded derivatives are fairly new in the energy markets, structures and contracts with derivative characteristics have existed well before the introduction of the standardized contracts in Exchanges.

Energy markets are unique in a number of ways, with issues of storage, transport, weather, seasonality, politics, and technological advances playing a major role. In the 1970s, seven major oil companies (known as the "7 Sisters") owned 50% of the world's known reserves at the time, and produced two-thirds of its crude and products. Today, they own less than 10% and produce less than one-third of the products. Moreover, while OPEC used to be the major price-setter of oil, nowadays the marketplace is taking the lead with OPEC's role being somewhat less important. The members of OPEC include Saudi Arabia, Iran, Kuwait, the UAE, Venezuela, Indonesia, Nigeria, Algeria, Libya, Gabon, and Qatar. In addition, as mentioned previously, weather is a major factor for the energy markets. A profound example is the cold winter of 1989-1990 in the US, where heating oil was trading at 57c per gallon in November of 1989, and it hit $1.10 in January 1990. Moreover, according to Kleinman (2005), heating oil and gasoline have some unique seasonal tendencies, with 80% of the time making a bottom in March and then rising into May. In addition, the American Petroleum Institute (API) and the Department of Energy (DOE) by releasing weekly reports with supply and demand figures for the major energy products like crude, natural gas, gasoline, and heating oil, they can even move the electronic overnight market prior to next day's open.

Finally, international politics play a crucial role in energy markets, since oil is a strategic commodity and an economic necessity. The Arab Oil Embargo, the Iran-Iraq War, the two Gulf Wars, the Russian invasion in Georgia, the recent unrest in the majority of the Arab World, with civil wars erupting in Egypt, Libya and Syria among others, are just a few of the examples that show how politics can dramatically affect oil and other energy commodity prices.

What's more on energy, some of the energy derivatives contracts can be more complicated than those found in the financial markets, like the swing, recall, or nominational contracts. In addition, some of the energy derivatives are far more complex than anything else found in other markets, as for example the structures used to value energy assets like power plants and gas storage. This complexity frustrates practitioners' ability to create simple quantitative models able to capture all the essential characteristics of the market. Even the standard contracts like forwards, futures, swaps, and options are defined and settled differently due to their physical nature, as for example the non-storability of electricity. In addition, energy prices are driven both by the short-term conditions of storage (and non-storability in the case of electricity) and by the long-term conditions of future potential energy supply, a condition reflected on the energy forward prices.

The unique characteristics and underlying price drivers of the energy markets that make them so different from the money markets can be summarized in the following table:

Table 2-1: What Makes Energies Different?

Issue	Money Markets	Energy Markets
Maturity of market	Several decades	Relatively new
Fundamental price drivers	Few, simple	Many, complex
Impact of economic cycles	High	Low
Frequency of events	Low	High
Impact of storage and delivery; the convenience yield	None	Significant
Correlation between short- and long-term pricing	High	Low, "split personality"
Seasonality	None	Key to natural gas and electricity
Regulation	Little	Varies from little to very high
Market activity ("liquidity")	High	Low
Market centralization	Centralized	Decentralized
Complexity of derivative contracts	Majority of contracts are relatively simple	Majority of contracts are relatively complex

Source: "Energy Risk: Valuing and Managing Energy Derivatives", Pilipovic, D. (1998)

Being a relatively young competitive market, energy suffers from lack of historical spot and forward price information that could help establish a universal agreement of the fundamental price drivers and/ or the quantitative pricing methodologies. Adding to that, some of the energy contracts experience relatively small volumes of present-day market activity (referred to as "illiquidity"), which distorts the process of "price discovery" in the futures markets. Moreover, energy markets are highly decentralized introducing geographic "basis risk", in contrast to the financial markets that are centralized in terms of location, capital and expertise. Energy producers and end users are spread all over the world, and while many of them may actively use the NYMEX futures contracts to hedge their risks, these contracts represent prices at specific delivery points which might behave differently from the local markets being hedged.

Furthermore, the evolution processes of energy prices reveal some unusual characteristics like the extreme volatility. For example, the volatility of natural gas and electricity prices is in the 50%-100% and 100%-500% range, respectively, while the volatility of exchange rates and the S&P500 index is in the 10%-20% and 25%-35% range, respectively. In addition to high volatility, energy prices exhibit some interesting properties like mean reversion, seasonality, spikes, regime switching, stochastic volatility, and volatility smiles, which make the processes describing the price evolution unique. In addition, energy derivatives usually involve spreads and thus it is important to take the correlation of the joint distributions into account, in order to capture all the structural characteristics of the price processes.

The energy markets are a collection of commodities that are quite different in nature and according to Eydeland and Wolyniec (2003) can be sorted in the following three groups:

1. Fuels: oil, gas, coal, and their derivatives and by-products.
2. Electricity
3. Weather, emissions, and forced outage insurance

As mentioned previously, the fuel markets were the first ones to open for competition in the 80's, followed by electricity in the early and mid 90's, with the late 90's introducing the trading of new types of commodities like weather and emissions. The main focus of this research will be on the fuels; oil, gas and their by-products. We are going to touch upon electricity; however a very deep examination of the electricity markets as well as of the third group of energies (weather, emissions etc.) is out of the scope of this research. We will leave the later energy group for future research.

2.2. NYMEX energy products

Significant changes in supply, demand, and pricing have touched many of the world's energy markets the past few decades. Changing economic patterns, globalization, international politics, war, and structural changes within the world's energy industry have created significant uncertainty in the energy market, which leads to increased market volatility and the need for effective ways to hedge the risk of adverse price exposure. There are three major energy exchanges; the Intercontinental Exchange (ICE) (former International Petroleum Exchange) of London which trades actively Brent Crude Oil and refined products, natural gas, power and emissions, the Tokyo Commodity Exchange (TOCOM) which actively trades crude oil, gasoline and kerosene contracts, and lastly the predominant exchange, the New York Mercantile Exchange, Inc. (NYMEX). Nowadays, the most commonly used risk management instruments in the energy markets are the futures and options contracts listed on the NYMEX.

NYMEX was founded in 1872 by a group of dairy merchants. The company's two principal divisions are the NYMEX and the Commodity Exchange (COMEX), once separately owned exchanges. Today, NYMEX is owned by the CME Group that also owns the Chicago Mercantile Exchange and the Chicago Board of Trade. NYMEX is the world's preeminent trading forum for managing price risk in the markets of energy, precious metals, and North American copper. The first successful energy futures market was established at NYMEX in 1978 with the launch of the heating oil futures contract. For the last several years, NYMEX has been receiving an AA+ long-term counterparty credit rating from Standard & Poor's. Energy contracts mostly trade on the NYMEX and include physically delivered futures and options contracts for light sweet crude oil, gasoline, heating oil, and natural gas; propane futures; options contracts on the price differentials, or crack spreads, for gasoline/ crude oil, and heating oil/ crude oil; and the differentials between contract months, or calendar spreads for crude oil, gasoline, heating oil, and natural gas. The light, sweet crude oil contract, launched in 1983, is the most actively traded futures contract based on a physical commodity in the world.

The energy markets are available for trading for 23 ¼ hours a day from Sunday evenings through Friday afternoons. The physically delivered futures contracts are traded by open outcry and through the CME Globex electronic trading system, which is conducted through a technology services agreement with the Chicago Mercantile Exchange (CME). NYMEX also lists financially settled energy contracts on CME Globex. These include full-sized and fractional futures for NYMEX crude oil, heating oil, gasoline, and natural gas. In addition, NYMEX lists on the NYMEX ClearPort electronic platform from Sunday evenings to Friday afternoons a slate of approximately 300 energy and related contracts that replicate popular over-the-counter (OTC) transactions which can be traded or transacted off of the Exchange and submitted for clearing. These include refined products in the United States, Europe, and Asia; crude oil; natural gas; electricity; coal; emissions credits; and freight rates for petroleum shipments on principal world tanker routes.

One important metric to consider for understanding the importance of NYMEX and the recent growth in its oil futures' contracts trading is the total open interest; the total number of both long and short positions that are open at any given point in time. Total open interest for the oil futures alone has risen from 350,000 contracts in mid-1998 to 1,280,000 in mid-2008. Considering that one futures contract represents 1,000 barrels of oil, this represents a rise from 350 million barrels to 1.28 billion barrels within a decade. The only other major exchange for energy futures is the Intercontinental Exchange (ICE) that trades a highly liquid futures contract on Brent crude, and a contract pegged off the NYMEX's futures contract on WTI, both having a combined open interest of about 15% of the NYMEX open interest. Other exchanges around the globe also trade oil futures contracts based on different types and qualities of crude, but their total open interest would only be a small fraction of that from the NYMEX and the ICE.

2.3. Modelling approaches

2.3.1. Hedging with futures and price discovery

In the US, futures contracts have been used for more than a century in order to manage price risk. Hedging with futures eliminates the risk of fluctuating prices, however it also limits the opportunity for future profits should prices move favourably. Generally, hedging reduces exposure to price risk by shifting that risk to those with opposite risk profiles or to investors who are willing to accept the risk in exchange for a profit opportunity. In addition, it allows a market participant to lock in prices and margins in advance, reducing the potential for unanticipated losses. A perfect hedge is one that completely eliminates the market participant's risk. Nonetheless, because the cash and futures markets do not have a perfect relationship, in the real world there is no such thing as a perfect hedge, so there will always be some profit or loss. However, managing a hedge strategy should be an ongoing process. While hedges serve to stabilize prices, risk management targets should be re-evaluated in future periods as market and financial circumstances change.

When an individual or a company chooses to use futures markets to hedge a risk, the objective is usually to take a position that neutralizes the risk as far as possible. This can be achieved by using one of the two different types of hedge or a combination of them. The first type is the short hedge, which involves a short position in futures contracts and is more appropriate when the hedger already owns an asset and expects to sell it at some time in the future, or when the asset is not owned right now but will be owned at some point in the future. The other one is the long hedge, which involves taking a long position in a futures contract and it is more appropriate when the hedger knows that he will have to purchase a certain asset in the future and wants to lock in a price now. Moreover, long hedges can be used to manage an existing short position.

Two basic hedging strategies can be identified. The first one is known as the "offsetting hedge", where the main idea is to maintain a balanced book continuously; each physical deal must be balanced by an opposite futures transaction in order to offset the price risk. The second is to use hedges to lock-in an attractive price level and thus securitize certain profits on anticipated business. By locking-in a good price, speculation is being removed from the transaction, either by fixing the sales price at a level higher than known costs in the case of the seller, or by fixing the purchasing price at a lower level than costs in the case of the buyer.

As mentioned earlier, it is important to look at the bigger picture when hedging, because when using for example futures contracts it can result in a decrease or an increase in the hedger's profits relative to the position he would be in without hedging. A company that does hedge can expect its profit margins to be roughly constant when operating in an industry that competitive pressures make the prices of output goods, and services reflect the input costs. On the other hand, in such an environment, a company that does not hedge can expect its profit margins to fluctuate. Thus, one should take into account all the implications of price changes on a company's profitability when designing its hedging strategy in order to caution against price changes.

Moreover, an important concept in hedging is basis risk. The basis (b) is the difference between the spot price (S) of an asset and its futures price (F) [$b = S - F$]. The choice of the futures contract to be used is a key factor affecting basis risk, since in general, basis risk increases as the time difference between the hedge expiration and the delivery month increases. Overall, basis risk is created mostly due to the following reasons:

a. the asset whose price is to be hedged may not have exactly the same specifications as the asset underlying the futures contract
b. the hedger may be uncertain as to the exact date when the asset will be bought or sold
c. the hedge may require the futures contract to be closed out before its delivery month

Another important notion in hedging is the hedge ratio, which is the size of the position taken in futures contracts to the size of the exposure. In most cases, and especially when a cross hedging is used, a hedging that occurs when the two assets share some different characteristics, which is usually the norm, a hedge ratio of 1.0 is not always optimal. The optimal hedge ratio should be the minimum variance hedge ratio, which is the slope of the best-fit line obtained when changes in the spot price are regressed against changes in the futures price:

$$H = \frac{p\sigma_s}{\sigma_f} \tag{2.1}$$

Where H is the minimum variance hedge ratio, σ_s is the standard deviation in the change in the spot price, σ_f is the standard deviation in the change in the futures price, and p is the coefficient of correlation between the change in the spot price and the change in the futures price. Furthermore, in the case where there are no liquid futures contracts that mature later than the expiration of the hedge, a strategy known as "rolling" the hedge forward is appropriate. It involves entering into a sequence of futures contracts and when the first futures contract is near expiration, it is closed out and the hedger enters into a second contract with a later delivery month, and so on. This strategy results in the creation of a long-dated futures contract by trading a series of short-dated contracts.

In the case of the crack spreads, whether a hedger is selling or buying the crack, it reflects what is done on the product side of the spread. Purchasing a crack spread is the opposite of the crack spread hedge. It requires a short hedge in crude oil and long hedges in products. Refiners are naturally long the crack spread as they buy crude and sell products, however, sometimes they buy products and sell crude, thus finding it useful to purchase a crack spread. Such a case might occur when a refiner is forced to shut down due to repairing or any other reason, and thus is unable to produce enough products to meet term supply obligations. In such a case the refiner must buy products at spot prices for resale to his term customers in order to honour existing supply contracts.

Furthermore, lacking adequate storage space for incoming supplies of crude oil, the refiner must sell the excess on the spot market in order to honour existing purchase contracts. In the event that the refiner is forced to make unplanned entries into the spot market, and his supply and sales commitments are substantial, unfavourable market movements could eventually take him out of business. So, in order to protect himself from increasing product prices and decreasing crude oil prices, the refiner could use a short hedge against crude oil and a long hedge against products.

2.3.2. Futures pricing theory

In terms of the methodologies used for pricing commodity derivatives contracts, the arbitrage pricing approach is the most commonly used one, especially when pricing a futures contract. Whenever it is possible to construct a dynamically adapted portfolio that will perfectly replicate the payoff of the derivative contract, the absence of arbitrage forces the derivative price to be equal to the price of the replicating portfolio. In the case where it is always possible to build a dynamically adapted portfolio that will perfectly replicate any payoff, the market is said to be complete. In a complete market there will only be a single non-arbitrage price for any contingent claim, and a unique probability measure called the risk-neutral probability measure. This risk-neutral probability measure will be equivalent to the physical probability measure, under which the non-arbitrage price of any contingent claim is equal to the expectation of its payoff discounted at the risk-free rate.

However, this approach is not as straight-forward in its application when it comes to pricing energy derivatives. Difficulties with storage may prevent us from using the non-arbitrage arguments for derivatives pricing because one cannot create a replicating trading strategy involving the spot price, and thus there may not exist a unique risk-neutral equivalent probability measure. The following sections will describe the various theories underpinning the pricing of commodities futures, which can further be applied to pricing energy derivatives.

2.3.2.1 Commodity futures pricing

The pricing theory of futures for financial assets such as bonds and stocks is different than that of commodities. This section will describe the various theories underpinning the pricing of the commodities futures in the Energy market. The main difference with the pricing of financial futures contracts is that they rely on pure arbitrage arguments, whereas commodities are more complicated due to the fact that storage is costly and that spot markets may not exist or there are too thin for any arbitrage opportunities. In addition, futures contracts on commodities can be considered as investment assets, like gold and silver, and as consumption assets, like the energy commodities.

However, to be able to price any of the energy futures the following key assumptions need to be made, which according to Hull (1999) need to hold for at least some key market participants like the major investment banks:

1) There are no transaction costs.
2) All net trading profits are subject to the same tax rate.
3) Market participants can borrow and lend money at the same risk-free rate of interest.
4) Market participants take advantage of arbitrage opportunities as they occur.

Arbitrage opportunities disappear as soon as they occur given the fourth assumption. Therefore market prices are such as there are non-arbitrage opportunities. The first three assumptions are obviously not perfectly valid for commodities; however the degree of validity in each market is almost the same. Nevertheless, adjustments can be made to bring the model in line with "the real world". The main requirement is for the arbitrage assumption to hold. At the same time volatility is extremely high in the energy markets, which makes it difficult to forecast future prices. The major Pricing theories for commodity futures are the following:

2.3.2.2 Theory of storage

Inventories play a crucial role in the price formation in markets for storable commodities, which are also referred to as "cash and carry markets". The possibilities of storage imply that excess supplies can be carried over to future periods, and another perspective on the seasonal patterns inherent in the energy futures prices can be gained by applying the basic ideas from the theory of storage by Kaldor (1939), Working (1948, 1949), Brennan (1958), and Tesler (1958). The theory of storage explains the difference between current spot prices and futures prices in terms of interest foregone in storing a commodity, warehousing costs and a convenience yield on inventory. The relationship between futures and spot prices, in the context of the physical storage cost and the interest paid to finance the commodity less the income earned on the commodity, is known as the "cost of carry" relationship.

The convenience yield on a commodity can be defined as the flow of benefits which accrues to the owner of physical inventory but not to the owner of a contract for future delivery (Brennan, 1991). These benefits may include the ability to profit from temporary local shortages or the ability to keep a production process running. Moreover, spot prices are primarily driven by the fundamentals of the short-term market factors; however they still get influenced by the longer-term expectations of the equilibrium price levels. That is why we use the convenience yield (y) to explain the differences between short- and long-term price behaviour in the commodities markets. An example can be the fact that users are willing to pay a premium for near-term delivery in response to any supply shortages, especially in the energy markets. So in other words, the convenience yield is a measure of the balance between the available supply and the existing demand for the commodity.

The convenience yield represents the net value for holding the commodity, excluding any financing costs, and it can be positive when the benefit of having the commodity on hand is greater than the cost, or negative otherwise. It can also be regarded as comparable to the dividend obtained from holding a company's stock which can be expressed as follows:

$$y \simeq (S_t - L_t) + k, \quad with \quad y \to k \quad as \quad t \to \infty \tag{2.2}$$

Where, y is the convenience yield, S_t is the spot price, L_t the equilibrium price, and k a constant. Kaldor (1939) and Working (1948, 1949) both expected the convenience yield to depend inversely on the stocks of inventory of the commodity, a negative relationship known as the Kaldor-Working hypothesis (see Brennan, 1991). In addition, Dincerler et al. (2005), illustrate that there is a non-monotonic relationship between withdrawals from inventories and convenience yields for crude oil and natural gas. They show that increased demand elevates convenience yields until a threshold is reached, at which point stocks are withdrawn from inventory. On the other hand, if there is abundance of stocks and they eventually cross a critical level, again stocks will be withdrawn to discharge their storage costs.

Assuming that the convenience yield of the commodity can be written as a function of the output price alone and that the interest rate is non-stochastic, then there can be a deterministic relation between the spot and futures price of the commodity. According to the theory of storage (or stockpiling), which again is based on traditional arbitrage pricing, the futures price $F_{t,T}$ of a contract expiring at period T observed at time t is given by:

$$F_t = S_t e^{(r+u-y)(T-t)} \tag{2.3}$$

Where the current spot price S_t is being compounded by the interest rate r, the convenience yield y, and the storage cost as a proportion u of the spot price, for the period until expiration of the contract $(T-t)$. The above formula was introduced by Brennan and Schwartz (1985) in their pioneering research for the valuation of commodity derivatives. The convenience yield measures the extent to which the spot price compounded with the interest rate plus the cost of storing the commodity exceeds the futures price. It mainly holds for consumption assets and not for investment assets, because the owner is more reluctant to sell the commodity and buy futures contracts which cannot be consumed. Hence it could be argued that the convenience yield reflects the market's expectations concerning the future availability of the commodity. The greater the possibility of shortages will occur during the life of the futures contract, the higher the convenience yield.

Moreover, according to Brennan and Schwartz (1985) the convenience yield will depend on the identity of the individual holding the inventory and on equilibrium inventories held by individuals for whom the marginal convenience yield net of any physical storage costs is highest. However, direct empirical evidence on the theory of storage has been limited due to the scarcity of reliable storage data. Fama and French (1987 & 1988) and Casassus and Collin-Dufresne (2005) study indirectly the theory of storage by testing its implications, without using inventory data. Only Brennan (1991), shows direct evidence in his study of a declining marginal convenience yield on inventory, which is however limited to agricultural commodities and does not explain explicitly how much of the variation in the convenience yield can be attributed to inventories.

2.3.2.3CAPM and the theory of risk premium

The Capital Asset Pricing Model (CAPM) is a set of predictions regarding equilibrium expected returns on risky assets, and was developed by Sharpe (1964), Lintner (1965), and Mossin (1966), in their subsequent articles. The CAPM is based on some simplifying assumptions that according to Bodie et al. (2005) can be summarized in the following list:

1. There are many wealthy investors holding endowments that are relatively small compared to the total endowments (perfect competition assumption).
2. All investors plan for one identical holding period (myopic behaviour).
3. Investments are limited only to publicly-traded financial assets, and to risk-free borrowing and lending arrangements.
4. Investors pay no taxes on returns and no transaction costs.
5. All investors are rational mean-variance optimizers.
6. All investors share the same economic view of the world and analyze securities in the same way (homogeneous expectations assumption).

According to the CAPM, the higher the risk an investor bears for an investment, the higher the required return. Moreover the CAPM assumes that there are two types of risk in the economy: systematic and non-systematic. Non-systematic or specific is the risk that is common to a class of assets and hence can be eliminated in a well-diversified portfolio. Systematic Risk on the other hand, is the risk that cannot be diversified away and arises from the correlation of that asset's returns and the returns of the market as a whole. That is why stocks have a tendency to move together leaving investors exposed to some residual risk although they might hold a diversified portfolio of stocks. Hence, an investor will demand a higher expected return than the risk-free rate, in order to bear the additional systematic risk.

The CAPM implies that as individuals attempt to optimize their personal portfolios, they each arrive at the same portfolio, with weights on each asset equal to those of the market portfolio. Therefore according to the CAPM theory the expected return on the asset is the risk-free rate plus an expected premium for bearing that extra risk, which can be presented in a one-period scenario by the following formula:

$$E(R_i) = R_f + \left(E(R_m) - R_f\right)\frac{Cov(R_i, R_m)}{\sigma^2(R_m)} = R_f + \left(E(R_m) - R_f\right)\beta_i \tag{2.4}$$

$E(R_i)$: Expected Return on the i_{th} asset

$E(R_m)$: Expected Return on the market

R_f: Risk-free rate of return

$Cov(R_i, R_m)$: The covariance of the returns of the i_{th} asset and the market

$\sigma^2(R_m)$: Variance of market returns

β_i: Systematic Risk of the i_{th} asset

Moreover, the equation for the one-period expected return on an asset is:

$$E(R_i) = \frac{E(S_{iT}) - S_{i0}}{S_{i0}} \tag{2.5}$$

S_{i0} : The price of the i_{th} asset now

$E(S_{iT})$: The expected price of the i_{th} asset at time T

Therefore, solving equations (2.4) and (2.5) for the price of the asset, we get:

$$S_{i0} = \frac{E(S_{iT}) - \left(E(R_m) - R_f\right)S_{i0}\beta_i}{\left(1 + R_f\right)} \tag{2.6}$$

The above equation provides us with a formula for the futures price, which allows an investor to buy an asset now but defer the payment for one-period. Hence, the current price of a future F_{iT} will be the spot price of the asset multiplied by its future value factor:

$$F_{iT} = S_{i0}\left(1+R_f\right) = E(S_{iT}) - \left(E(R_m) - R_f\right)S_{i0}\beta_i \tag{2.7}$$

The CAPM theory leads to an alternative way of estimating the futures prices on commodities than the classical theory of storage. More specifically a scenario in continuous time can give the fair price of a futures contract. Consider a speculator who takes a long futures position in the hope that the price of the asset will be above the futures price at maturity. In addition, let's assume that the speculator puts an amount equivalent to the present value of the futures contract into a risk-free investment at time *t* while simultaneously takes a long futures position. The proceeds of the risk-free investment are used to buy the asset on the delivery date, at time T. The asset is then immediately sold for its current market price. This means that the cash flows to the speculator for time t and T are $-Fe^{-r(T-t)}$ and S_T respectively, where S_T is the price of the commodity at time T. Hence, the present value of the investment at time t is:

$$PV_t = -F_t e^{-r(T-t)} + E(S_T)e^{-k(T-t)} \tag{2.8}$$

That is to say that the present value of the investment at time t, is the present value of the money that will be given to settle the futures position at T, plus the expected price of the commodity at time T, discounted by an appropriate rate k for the investment. That means that k represents the expected return required by the speculator on the investment. Assuming that all investment opportunities have a net present value of zero (otherwise arbitrage opportunities arise), the fair price of the futures in the risk neutral world is:

$$F = E(S_T)e^{(r-k)(T-t)} = E(S_T)e^{-p(T-t)} \tag{2.9}$$

The value of k depends on the systematic risk of the investment that was discussed in the CAPM setting and hence the term p represents the risk premium. One way of explaining the risk premium would be to look at the conditions within the specific commodity market. An increased demand from risk adverse producers to hedge their products in the futures market would probably result in futures prices being lower that the expected future spot price, hence $p > 0$. The opposite relation will occur when the demand side is the most risk averse. A second way of explaining the risk premium is to consider the futures contract as a financial asset and compare it to other assets in the stock market. Hence, if the return on the futures contract is positively correlated to the level of the stock market, holding the contract involves positive systematic risk and an expected return above the risk-free rate is required leading to $p > 0$. This price theory can also be applied in markets where the commodity is perishable.

Based on all the above let's note what the major pros and cons of the theory of storage and the CAPM are. The non-arbitrage argument underlying the theory of storage cannot be applied to non-storable commodities, as there is no possibility of obtaining a risk-free position by buying the commodity in the spot market and selling it in the futures market. Thus, the market is said to be incomplete, as the number of assets traded is not equal to the sources of risk, hence no risk-neutral strategies are identified. Furthermore, the CAPM approach argues that systematic risk should be important in the pricing of futures contracts, but leaves out storage costs and convenience yields. On the other hand, the theory of storage ignores the possibility that systematic risk may affect the equilibrium prices of commodity futures contracts.

2.3.2.4 Expectations hypothesis, backwardation, and contango

There are three traditional theories that explain the relationship between the futures price and the expected value of the spot price of a commodity at a future date; expectations hypothesis, normal backwardation, and contango. The expectations hypothesis states that the expected profit to either position of a futures contract would be equal to zero. This means that the futures price equals the expected value of the future spot price of the commodity:

$$F = E(S_T) \tag{2.10}$$

The aforementioned hypothesis relies on risk neutrality, which argues that all market participants should agree on a futures price that provides an expected profit of zero to all parties. In a risk-neutral world, investors require no compensation for risk, and the expected return on all assets is the risk-free rate. This hypothesis can bear a resemblance to market equilibrium in a world with no uncertainty, but it ignores any risk premiums that must be built into the futures prices when the future spot prices are uncertain.

On the other hand, if storage costs and convenience yields are very low or alternatively when there is a positive risk premium $(p > 0)$, then for some commodities one can predict that prior to delivery the futures price is below the expected future spot price:

$$F < E(S_T) = S_t e^{r(T-t)} \tag{2.11}$$

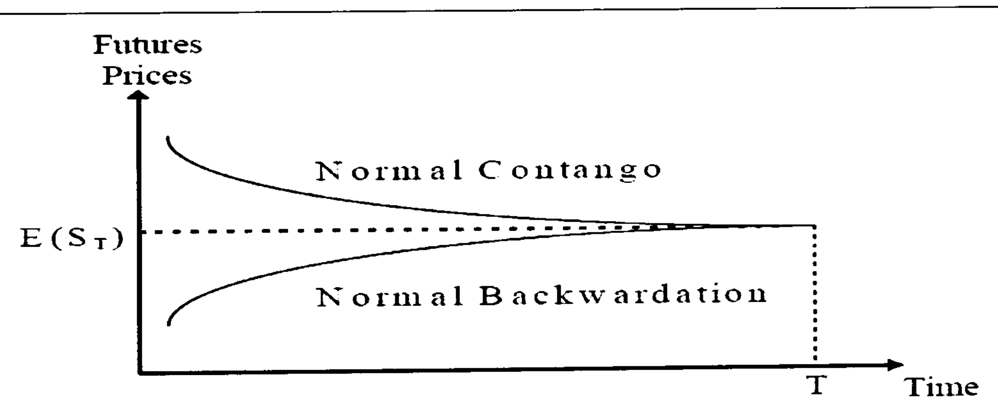
This relationship is called normal backwardation and was proposed by Keynes (1930). The origin of the idea is that producers (e.g. farmers) normally wish to hedge their risk by shorting the commodity, and consumers on the other hand go long on the futures markets. So if the producers were under stronger hedging pressure, they would dominate the market and would be net short. In addition, since there are risks associated with being long, Keynes hypothesized that hedgers would have to entice the speculators by making the expected return from a long position greater than the risk-free interest rate. The futures price will rise (on average) through time until, at delivery, the futures price equals the spot price. This argument indicates that futures would be downward biased predictors of the corresponding future spot prices. Hicks (1946) later maintained a similar point of view. Yet, although this theory recognizes the importance of risk premiums in futures markets, it is based on total variability rather than on systematic risk. This comes at no surprise since Keynes developed this theory almost 40 years before the modern portfolio theory was developed, which refines the measure of risk used for the risk premiums.

Subsequent development of this topic in the literature explained that hedgers would also prefer long positions to reduce their risk under certain circumstances (Cootner, 1960). If hedgers need to go long, or if the convenience yield (or the risk premium) is negative owing to oversupply, then the hedgers must pay a premium for futures contracts in order to induce speculators to go short. This requires the futures price to be greater than the expected spot price (Copeland and Weston, 1992):

$$F > E(S_T) = S_t e^{r(T-t)} \tag{2.12}$$

In the latter case, futures would over-predict the future spot prices and this bias would be the risk premium that speculators would require to provide "insurance" to the commodity traders. Thus, a speculator who sold short a futures contract at a price *F*, would expect to be able to buy it back on (or near) the delivery date at a lower price, $E(S_T)$. This relationship has been referred to as normal contango. So, based on the risk premium theory, backwardation or contango could occur depending on whether speculators were "net long" or "net short", a situation that could be attributed to seasonal phenomena (O' Brien and Schwarz, 1982). In the same lines, according to Anderson and Danthine (1983), normal backwardation and contango can arise as a result of the inequality between long and short hedging positions, a situation that requires the existence of speculators to restore equilibrium. That is the main concept behind the idea that futures contracts provide insurance to hedgers by ensuring the transfer of price risk to speculators. Normally, the amount that net hedgers are willing to pay as insurance would be equal to the premium earned by the speculators for bearing the risk. Figure 2-1 shows the expected price development for a futures contract under the normal backwardation and the normal contango hypothesis, with the price declining with maturity for the former, and rising with maturity for the latter.

Figure 2-1: Illustration of Normal Contango and Backwardation situations.



Source: Options, Futures and other Derivatives, Hull (1999).

Brennan and Schwartz (1985) as well as Gibson and Schwartz (1990) argue that backwardation is equal to the present value of the marginal convenience yield of the commodity inventory. In addition, Litzenberger and Rabinowitz (1995) have presented evidence for the case of crude oil, that slowly increasing, and sufficiently fast decreasing extraction costs, can support weak and strong backwardation, respectively. They also find that production at full capacity may explain backwardation as well. On the other hand, they find that when the price of oil is low and marginal producers are losing money, in order for them to maintain the option to produce in the future, the oil market could be in contango.

2.3.2.5 Which theory is more appropriate for energy?

Energy products have some unique characteristics that make them different than most commodities. For example, electricity is "non-storable", at least not in sizeable amounts in the case of hydro storage, and in the case of indirectly storing the raw materials for producing electricity (e.g. coal, oil, natural gas etc.) this approach is uneconomical due to the high storage costs and the technological complexity of storing some of them (e.g. natural gas). In addition, electricity has some unique physical requirements in order to achieve the instantaneous equilibrium between local demand and supply. Similar arguments apply also for natural gas which is currently very expensive and technologically difficult to store in large amounts. Hence the arbitrage across time and space, based on the storage theory and transportation, is limited for some of the energy products, if not completely eliminated for a few of them.

After studying all the features of the various energy markets and the major research done in the field, it can be concluded that energy can be characterized more like a price discovery market, which turns in favour for the theory of risk premium. A risk premium could arise if either the number of participants on the supply side differs substantially by the number on the demand side, or if the degree of risk aversion varies considerably between the two sides.

2.4. Commodity indexes: the case of energy

2.4.1. The evolution of indexes

Most market investors, and even index investors themselves, prefer to use index data to predict or speculate on the next market move, as the purpose of indexes since their inception was to track and analyse the respective market or sector. Indexes initially have been used as a marketing tool from publishing houses in their effort to attract more readers. One of the first stock indexes, the Dow Jones Industrial Average, that traces its origin back to the end of the 19^{th} century, was marketed and published by the Wall Street Journal. The S&P 500 started back in 1926 as a 90-stock index, by The Standard Statistics Bureau, a publisher of investment information reports, while the FTSE index began as a 30-stock index in the 1930s and it was published by the Financial Times. Since then, indexes have become essential tools for evaluating investments and investment managers, giving birth to index benchmarking since they can provide valuable information as to who is able to beat the market. Indexes have also been used as the core of many mutual funds investment strategies, with the most recent years being used for the creation of ETFs, and now ETNs, ETCs, ETVs and other similar investment vehicles. In general, there is a transition in the use of indexes observed lately, from benchmark tools to trading vehicles. ETFs that bring index funds into tradable units continue to expand in terms of both number and assets under management, seriously challenging mutual funds.

More specifically, indexing is a very powerful tool for equity investing, as it is one of the least expensive ways available and is very transparent. In addition, as it is widely documented in the literature, index investing, in the long run, outperforms active investing. As the famous CAPM suggests, a broad cap-weighted market index is an efficient equity investment as ordinary investors cannot outperform it without exceptional skills or information. This wide acceptance of the importance of index investing can be verified by the increasing number of new indexes not only for equities, but also for alternative investment classes such as commodities. Nowadays, indexes can be considered as investment strategies on their own, with ETFs based on specialized indexes, replacing custom portfolios with active managers. The spectrum of indexes is so broad reflecting almost all available sectors, industries, and investment themes such as traditional or alternative energy. Moreover, building on the notion that it is very efficient and attractive to construct tradable securities and instruments on top of various indexes, there is a plethora of ETFs that combine various asset classes, or construct indexes with selective stocks or different weights on the various securities. Also, because of the fact that ETFs rely primarily upon indexes, they have better performance along with lower fees, and increased transparency.

2.4.2. Commodity indexes

Commodity indexes have been around for many years and as is the case with all early equity indexes, they were used mostly for benchmarking and to track spot commodities process. One of the first published commodity indexes is the Economist's Commodity-Price index that started in 1864. Then, in 1957 the Commodity Research Bureau (CRB) Index was established, tracking spot commodity processes, and after undergoing major revisions in its composition it is still published today. Nevertheless, it is in the past 20 years that the development of commodities indexes has witnessed tremendous changes. The first generation of investable commodity indexes appeared only in 1991 when the S&P GSCI (originally the Goldman Sachs Commodity Index) is introduced. A few years later, in 1998, the Dow Jones-UBS Commodity Index (originally the Dow Jones-AIG Commodity Index), and the Rogers International Commodities Index (RICI) are both launched. Both the S&P GSCI and the RICI indexes are heavily weighted towards the energy sector, while the Dow Jones-UBS, because of the rule that no sector can weigh more than one-third of the index, has energy at its limit; in many instances this limit is over exceeded between the annual rebalancing periods.

The common characteristic, and a major disadvantage of these early indexes is that they invest in commodity futures contracts that are close to expiration, thus they roll forward their futures positions more frequently which makes it very expensive to follow an index replication strategy using exchange-traded futures (Gorton et al., 2008). In addition, as it is documented in Dunsby and Nelson (2010), holding a long futures position via an index that invests in the front of the curve is sub-optimal, especially in recent years, because many commodity futures curves have been experiencing steep contango at the front end of the curve, thus also diminishing the returns of the various investment products that are based on the respective index. Gordon (2006) presents a comprehensive overview of six of the most known first generation commodities indexes, explaining the underlying markets' selection process, their respective weights, and the index calculation methodology. It is shown that correlations between the indexes over long periods of time are quite high, even though they have many differences in terms of their construction methodology.

This previous observation was the main driver for the creation of the so called second generation commodity indexes such as the UBS Bloomberg Constant Maturity Commodity Index and the JP Morgan Commodity Curve Index. Both of these indexes have a constant weighting scheme across commodities, but their investments allocation is spread across several contract expirations within individual commodities. In the same context is the approach of the DJ-UBSCI 3 Month Forward index, which invests in contracts farther out the futures curve, reducing the effect of backwardation or contango as the curve tends to be flatter for longer maturities. These type of indexes outperform the first generation indexes because when the front end of the curve is in steep contango, as it is recently the case with crude oil, the losses tend to even out across the longer maturity contracts. Nonetheless, the opposite happens when futures markets are in backwardation, since the concentration usually occurs at the front-end of the curve. It can be argued however that the chronology of the indexes has a significant impact on their construction methodology, and hence their performance, as the most recent ones had the benefit of improving on the methodology used by previously developed indexes.

The latest addition to the family of commodities indexes is the so called third generation indexes that attempt to improve the returns of the previous two by incorporating commodities selection; overweight or include only commodities that are expected to deliver higher returns in the near future, while underweighting or omitting completely commodities that are expected to perform poorly. The UBS Bloomberg CMCI Active Index introduced in 2007 and the SummerHaven Dynamic Commodity Index introduced in 2009, are two examples of the third generation commodity indexes. The latter index includes 14 equally weighted commodities from a total of 27, rebalancing its futures portfolio every month using basis and momentum to identify the greatest possible risk premium. The former index uses a discretionary approach of its research analysts who, according to their view adjust the component weightings of the index. However, these types of indexes carry with them a major disadvantage since the method or the research analysts used to select the commodities and their respective weightings can be unsuccessful, and thus underperform passive indexes.

As mentioned above, because there are plenty of key differences in terms of their construction methodology amongst the commodity indexes, it is critical for investors to be aware of these differences. The first one concerns the various methodologies for weighting the indexes, such as liquidity- or production- based weights, arithmetic or geometric calculations. In addition, each index has different rules for rolling forward its futures contracts, from the next-month to a more distant contract.

2.4.3. Exchange Traded Funds (ETFs)

An Exchange Traded Fund (ETF) is an investment vehicle that tracks a market index, typically comprised by stocks, and trades on an exchange. ETFs were initially developed in the US[5], to accommodate institutional investors to trade a basket of securities in a single transaction, and to make stock program trading available to retail investors. With the recent massive growth in product offerings and liquidity, ETFs today can execute almost any

[5] An ETF is an investment company registered with the US SEC in the same way as a mutual fund or any other open-end fund. That is because it holds a portfolio of securities and its shares are continuously issued and redeemed at the daily Net Asset Value (NAV).

investment strategy. Index-linked ETFs are a perfect fit for the core holdings in a core-satellite investment strategy, while at the same time allowing for the employment of satellite investments via shorter-term tactical strategies such as stock, sector, style, or country over-weights. Nowadays they have expanded outside the traditional securities spectrum into non-traditional asset classes, such as commodities; in these cases they are known as Exchange Traded Vehicles (ETVs). These new investment vehicles not only serve the increasing needs of institutional investors around the world, but most importantly allow retail investors to enter an institutional space, that so far they have been excluded from, in terms of competitive pricing and efficiencies. Moreover, market niche indexes have been increasingly popular lately amongst investors, thus making the spot energy index an ideal candidate for the construction of an ETF that will follow the energy markets.

A commodity ETF, also called an Exchange Traded Commodity (ETC), is an investment vehicle that tracks the performance of an underlying commodity index, ranging from a single commodity or an ever-increasing number of commodities including energy, metals, softs and agriculture. ETCs trade and settle exactly just like normal shares, they are simple and efficient, have market maker support with guaranteed liquidity, and provide investors with exposure to commodities. Generally, ETCs are index funds tracking non-security indexes. The first funds that came into existence actually owned the physical commodity[6] (e.g. gold and silver bars). However, as it is difficult or even in some cases of non-storability (e.g. electricity) impossible to own the commodity, most ETCs now implement either a futures trading strategy, which may lead to quite different performance from owning the actual commodity, or equities trading strategies. ETCs that follow a futures commodity index, in order to maintain a long position need to continuously roll forward the front-month futures contract on almost a monthly basis. This process makes investors subject to transaction costs and other risks involved with the different prices along the term structure. The latter is the main reason that most of the recently created ETCs, and especially the largest ones by market capitalization, use stocks and not futures contracts to track the commodity index under consideration.

Nonetheless, ETFs have numerous advantages over traditional investments. First, style and sector ETFs can be applied into almost any tactical investment strategy or complete parts of

[6] The first gold ETF was the Gold Bullion Securities launched on the ASX in 2003, and the first silver ETF was iShares Silver Trust launched on the NYSE in 2006.

an existing portfolio. Broad-based ETFs, on the other hand, can act as diversified core holdings, either as stand-alone tools or as part of an investment strategy. They can be bought along with stocks, privately managed assets, and other investment products. Second, they can provide international diversification while at the same time having lower internal transaction and processing costs, as ETFs typically have low portfolio and investor turnover. Index-linked ETFs are the least expensive amongst the available investment products, as passively managed funds tend to outperform their actively managed peers. Third, index-linked ETFs can be shorted without an uptick, which gives extra flexibility to investors for hedging and market-timing strategies. Fourth, they are available throughout the day to all investors at market prices, as they are traded on an exchange, while they can also be bought on margin or make use of limit and stop loss orders. Finally, indexed-linked ETFs that are passively managed are more tax efficient than their actively managed peers because of the smaller portfolio turnover and smaller realization of capital gains. During a market downfall, participants in open-end mutual funds usually tend to close their positions to reduce exposure and/ or capture any gains that in turn may create capital gains' tax liabilities. These tax liabilities are then passed on to the remaining shareholders of the fund. On the other hand, ETFs can reduce such tax liabilities through an internal redemption mechanism where baskets of stocks, and not cash, change hands between investors. Under the US tax regime (and that of many other developed countries) this process is not taxable as there are no actual capital gains that need to be distributed to the ETFs' shareholders.

All the above mentioned advantages of commodity ETFs and ETNs have recently led to a plethora of such funds, which track passive benchmarks of commodity and energy sector equity indexes to come to the market. Energy commodity investing could be considered as a new style investment, with these tracking funds making it easier for a retail investor to obtain exposure to commodities, having at the same time a number of advantages over traditional debt instruments (notes, bonds, certificates). They can be used by the energy industry market players to complete parts of their existing portfolio, to perform tactical strategies, for hedging energy investment risk, portfolio diversification, or as a control measure of inflation exposure. The investment approach proposed in this thesis, of tracking the performance of the energy sector with stocks selected by two innovative evolutionary algorithms, promotes a cost effective implementation and true investability. While many funds cannot invest in commodities directly as in the case of pension funds[7], where governments in their effort to protect peoples' savings strictly regulate the industry by placing stringent restrictions on the types of assets held, they can now track the performance of a proposed Spot Energy Index (SEI) by investing in stock baskets selected by the evolutionary algorithms used. To that end, lately there are many investment houses around the globe that use evolutionary algorithms for tactical asset management strategies.

Although the proposed energy index represents the economic importance of the energy group of commodities to the global economy, it primarily serves as a performance benchmark given the limited ability for a direct investment. Nevertheless, the suggested approach provides investors with an option to track that performance of this Spot Energy Index using a basket of equities that are liquid and fully investable. This new style investing into the SEI, by selecting an optimal portfolio of stocks, can be particularly attractive to institutional investors. As stated in Barberis and Sheleifer (2003), style investing is attractive because institutional investors act as fiduciaries and thus they must follow systematic rules of portfolio allocation, and because of its simplified performance evaluation process. Hence, the work and findings presented in this thesis can encourage asset and fund managers to recognise the importance of the energy sector and prompt them to set-up similar Exchange Traded Funds that will track the constructed Spot Energy Index.

To that end, the proposed methodology suggests an effective, and at the same time, least expensive way to operate such a fund, giving the full flexibility of any investment style, long or short, that equities can provide. It provides with a low cost – compared to actively managed funds – means of accessing the energy spot markets. In particular, investors that cannot physically hold the energy commodities can benefit from the selected equity baskets that allow for both long and short position to be taken. Most commodity trading advisors and commodity pool operators use investment strategies that can be long-only or systematic long/short, using leverage to take the short positions. Hence, an effective index tracking strategy, as the one proposed in this thesis, should allow for both the replication of the performance benchmark index, and the implementation of this long/short strategy that can significantly improve the risk/ return profile of traditional asset portfolios.

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[7] Usually futures contracts and other derivative products in alternative investments such as commodities are excluded from their portfolios (Nijman and Swinkels, 2003).

Chapter 3.

3. Modelling energy spot prices: empirical evidence from NYMEX

This chapter investigates the behaviour of spot prices in eight energy markets that trade futures contracts on NYMEX, and of a geometrically weighted Spot Energy Index, proposed for the first time in this thesis. Two types of models are considered, a mean reverting model, and a spike model with mean reversion that incorporates two different speeds of mean reversion; one for the fast mean-reverting behaviour of prices after a jump occurs, and another for the slower mean reversion rate of the diffusive part of the model. These models are also extended to incorporate time-varying volatility in their specification, modelled as a GARCH and an EGARCH process. Finally, the relative goodness of fit of the different modelling variations is compared using Monte Carlo simulations.

3.1. Introduction

Over the past decade significant changes have taken place in the world's energy markets. Changing economic patterns, globalization, international politics, war, technological advances and structural changes within the world's energy industry, have resulted in a volatile market environment which also increased the need of market participants for risk management using derivative contracts such as futures and options. In this volatile market environment, it is important for market participants to use risk management models that can capture the most significant risks in the market. However, due to the unique features of energy markets, the traditional approaches for modelling prices that are used in financial markets are not applicable. For instance, energy prices exhibit extreme movements and volatility over short periods of time and may also be characterized by spikes which occur due to short-term supply or demand shocks. In addition, energy prices have the tendency to mean-revert to a long-run equilibrium level. Given these stylized facts, the assumption used in the Black-Scholes-Merton model (Black and Scholes, 1973; and Merton, 1973) that the underlying asset follows a log-normal random walk may not be appropriate.

The mean-reverting process has been considered by many academics and practitioners as the natural choice for commodities. The reason is that, according to microeconomic theory, in the long run a commodity's price should be tied to its long-run marginal production cost; that is it tends to revert back to a "normal" long-term equilibrium level. There is a wealth of papers in the literature that confirm mean reversion in spot oil prices based on strong empirical evidence, such as Gibson and Schwartz (1990), Brennan (1991), Cortazar and Schwartz (1994) and Schwartz (1997). Evidence of mean reversion for energy and agricultural commodities comes also from the futures markets, e.g. Bessembinder et al. (1995), Baker et al. (1998), and Pindyck (1999). In addition, the analysis of volatility of asset prices is a research area that has been widely examined over the years by numerous studies, unveiling a number of stylized facts. According to Engle and Patton (2001), a good volatility model should be able to capture the most important stylized facts of an asset's volatility, which are mean reversion, volatility clustering, and persistence, the latter measured by calculating the volatility's half-life. Intuitively, it would be expected to find that the innovations of the log-price series for all energy markets exhibit volatility clustering, and also that they have an asymmetric impact on the price volatility, with this asymmetry attributed to a leverage or risk premium effect.

In their study, Baumeister and Peersman (2008), when examining crude oil prices they found that positive shocks, due to shifts in global demand, have greater impact on price volatility compared to negative shocks, which can be attributed to supply disruptions. This observation is consistent with the presence of an "inverse leverage" effect (Geman, 2005), which is also evident in the natural gas prices examined by Kanamura (2009), and in hourly electricity prices from Northern California examined by Knittel and Roberts (2005) using an EGARCH (1,1) model. Eydeland and Wolyniec (2003) in their study on a number of energy markets, also conclude that an "inverse leverage" effect should be expected. Hence, in the case of the energy markets examined, it is expected that positive price shocks will have a greater impact on volatility than negative ones, an observation known as "inverse leverage effect" (Geman, 2005); for instance, Knittel and Roberts (2005) find the presence of an "inverse leverage effect" when modelling hourly electricity prices from Northern California using an EGARCH (1,1) model. Identifying any asymmetric tendencies in the volatility of the energy markets under investigation, using the EGARCH specification, can result in more efficient risk management applications by market practitioners and may also enhance the accuracy of various widely used risk management techniques, such as Value-at-Risk (VaR). Since volatility is an unobservable market variable, it is important to get the most accurate estimate in order to optimize the risk management models used and eventually determine the best possible hedging strategies.

Considering the above, the motivation for this research mainly stems from the existing controversies in the empirical literature, as to which modelling approach is best for, describing the behaviour of energy spot prices and capturing their risk characteristics. As a sound understanding of the stochastic dynamics of energy prices is a prerequisite for making an investment into energy commodities, a thorough empirical analysis is carried out by examining the performance, in terms of explanatory power and goodness of fit, of models that incorporate mean-reversion and spikes in the stochastic behaviour of the underlying asset. Two types of models are considered: a mean reverting model, where prices have the tendency to revert to their long-run mean, and a spike model that incorporates two different speeds of mean reversion to capture the fast mean-reverting behaviour of returns after a jump occurs and the slower mean reversion rate of the diffusive part of the model. These models are also extended to incorporate time-varying volatility in their specification, modelled as a GARCH and an EGARCH process.

This chapter contributes to the existing literature on modeling energy prices (see among others, Dixit and Pindyck, 1994; Schwartz, 1997; Clewlow and Strickland, 2000; Lucia and Schwartz, 2002; Cartea and Figueroa, 2005; Geman and Roncoroni, 2006; Cartea and Villaplana, 2008, Askari and Krichene, 2008) by expanding the choice of available models and the number of energy markets that these models are applied on. Spot prices of the eight most traded energy futures contracts on NYMEX and the constructed spot energy index (SEI) are used, covering the crude oil and all its by-product fuel markets, the soaring - due to their increased environmental importance - natural gas and propane markets, one of the most liquid electricity markets, and an index that represents the overall spot energy sector. The performance of each model is assessed on the basis of how well it can capture the trajectorial and distributional properties of the real market process. To compare the aforementioned processes and identify which one describes the data best, Monte Carlo simulations are run to replicate the price paths, and then test the goodness of fit of the models using a variety of both quantitative and qualitative tests. Moreover, a contribution in the existing literature is made by providing detailed information on the jump detection process, formally testing for any clustering effect, correlation pattern among commodities, and seasonality in the jump occurrence for all eight energy markets. This way, a better understanding is provided of how energy markets behave, what is the best modelling approach for each individual spot market and, consequently, the best model for the pricing of the relevant futures and options contracts. Identifying the correct dynamics for the energy prices is of great relevance for hedging, forecasting, and policy making in the energy markets. A further contribution to the literature is the empirical testing of which model can sufficiently capture and describe the dynamics of the two 1-1 crack spreads of crude oil with fuel oil and gasoline that trade futures contracts on NYMEX. From the perspective of a petroleum refiner who operates between the crude oil and the refined products markets, modelling accurately the dynamic behaviour of the two crack spreads and their constituents is of utmost importance, since unexpected changes in the prices of the crude oil or the refined products can significantly narrow the spread and put refiners at enormous risk.

The structure of this chapter is as follows. The next section presents the methodology used for modelling the spot energy markets under investigation and estimating the parameters for calibrating the models to real market prices. In section 3, the data and their properties are described. Section 4 offers empirical results, while section 5 evaluates the performance of each model in terms of matching the actual spot price behaviour. Finally, section 6 concludes this chapter.

3.2. Mean-Reverting Jump Diffusion GARCH/EGARCH Model

As already established, mean reversion is a main feature of energy commodities' event behaviour. In addition, energy prices often exhibit unexpected and discontinuous changes, so it is more appropriate to combine mean reversion and jump diffusion into the same model. The inclusion of spikes in the model is also justified by the existence of fat tails in the daily energy prices which suggests that the probability of rare events is much higher than the one implied by a Gaussian distribution; see for instance Cartea and Figueroa (2005) for a discussion on this in the UK power markets. According to the empirical findings presented in the literature, the presence of both excess skewness and kurtosis in all energy price returns suggests that a jump-diffusion model is more appropriate for both derivatives valuation (e.g. options pricing) and risk management purposes (e.g. VaR applications). Askari and Krichene (2008) point out that when jumps are added to oil price returns in a diffusion-based stochastic volatility model, sufficient variability and asymmetry in the short-term returns can be generated to match the skewness of implied volatility from short-term options. In their model, Clewlow and Strickland (2000) use the same speed of mean reversion for both spikes and normal shocks, inducing some persistence in the jumps especially when the mean-reverting coefficient is small. However, because the spikes represent a transitory phenomenon, after a jump has occurred prices do not stay at the high level to which they jump but tend to revert to their long-run mean. Consequently, when modelling energy prices it is also important to account for the fact that the decay rate of the jumps can be much faster than the decay rate of the diffusive component. This feature is incorporated in the model presented in this chapter by using two different speeds of mean reversion, a fast one after a spike has occurred and a slower for the normal (diffusive) shocks.

Another issue that needs to be addressed in the modelling methodology is the behaviour of volatility, which exhibits high values and clustering. Cartea and Villaplana (2008), in all three electricity markets that they examine, find that prices follow a strong seasonal component and thus a model with seasonal or time-varying volatility is preferable than one with constant volatility. Thus, in accordance with the empirical evidence from various studies related to the energy markets, a constant, as well as GARCH (Bollerslev, 1986) and EGARCH (Nelson,

1991) specifications for the variance are used. The proposed mean-reversion jump diffusion model, that incorporates the observed stylised facts of energy prices and their volatility, is based on Schwartz's (1997) one-factor model. The model is extended to allow for a deterministic seasonality as in Lucia and Schwartz (2002) and Cartea and Figueroa (2005). Log-prices are assumed that can be expressed as the sum of a predictable and a stochastic component as follows:

$$\ln S_t = f(t) + Y_t \tag{3.1}$$

with the spot price represented as:

$$S_t = F(t)e^{Y_t} \tag{3.2}$$

where $F(t) \equiv e^{f(t)}$ is the predictable component of the spot price S_t that takes into account the deterministic regularities in the evolution of prices, namely seasonality and trend. Also, Y_t is a stochastic process whose dynamics are given by the following equation:

$$dY_t = a_i(\mu - Y_t)dt + \sigma_t dZ_t + kdq_t \tag{3.3}$$

where a_i is the mean reversion rate, μ is the long-term average value of $\ln S_t$ in the absence of jumps, σ_t is the volatility of the series, dZ_t is a Wiener process, k is the proportional jump size and dq_t is a Poisson process. It is assumed that the Wiener and the Poisson processes are independent and thus not correlated, which further implies that the jump process is independent of the mean-reverting process.

Using equations (3.1) and (3.3), the modelling procedure by Dixit and Pindyck (1994) is followed and after applying Ito's Lemma, the proposed model can be discretised in the following logarithmic form:

$$\ln S_t = f_t + \left(\ln S_{t-1} * e^{-a_i \Delta t}\right) + \left(\ln \bar{S} - \frac{\sigma_t^2}{2a_i}\right) * \left(1 - e^{-a_i \Delta t}\right) + \sigma_t * \sqrt{\frac{1 - e^{-2a_i \Delta t}}{2a_i}} * \varepsilon_1 + J(\mu_J, \sigma_J) * I_{(u_t < \Phi \Delta t)} \tag{3.4}$$

where,

$$a_i = \begin{cases} a_1 = a_{JD}, \text{ when a jump occurs; for a duration equal to jump returns' half-life} \\ a_2 = a, \text{ otherwise} \end{cases} \qquad i = 1,2 \tag{3.4.1}$$

$$\sigma_t = \begin{cases} \sigma_t = \sigma \ [\text{Constant}] \\ \sigma_t = \sqrt{\beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 * \sigma_{t-1}^2} \ [GARCH(1,1)] \\ \sigma_t = \sqrt{e^{\beta_0 + \beta_1 * \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 * \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 * \ln(\sigma_{t-1}^2)}} \ [EGARCH(1,1)] \end{cases} \tag{3.4.2}$$

$$f_t = \gamma_0 \sin\left(\frac{2\pi(t+\tau)}{252}\right) + \gamma_1 t \tag{3.4.3}$$

$$I_{(u_t < \Phi\Delta t)} = \begin{cases} 1 \text{ when } u_t < \Phi\Delta t, \text{ i.e when a jump occurs} \\ 0 \text{ when } u_t > \Phi\Delta t, \text{ i.e when there is no jump} \end{cases}$$

$$\begin{aligned} &\mathrm{J} \sim N(\mu_J, \sigma_J) \text{ with Mean}: \mu_J = (\overline{\kappa}_J + \sigma_J \varepsilon_2) \text{ and Standard Deviation}: \sigma_J \\ &\varepsilon_1, \varepsilon_2 \sim N(0,1), \rho(\varepsilon_1, \varepsilon_2) = 0 \\ &u \sim U[0,1] \end{aligned} \tag{3.4.4}$$

where $\ln \overline{S}$ is the long-term mean (μ), Φ is the average number of jumps per day (daily jump frequency), $\overline{\kappa}_J$ is the mean jump size, σ_J is the jump volatility, ε_1 and ε_2 are two independent standard normal random variables, and u is a uniform [0, 1] random variable. The term $\mathrm{I}_{(u_t < \Phi\Delta t)}$ is an indicator function which takes the value of 1 if the condition is true, and 0 otherwise. This condition leads to the generation of random direction jumps at the correct average frequency. When the randomly generated number is below or equal to the historical average jump frequency, the model simulates a jump with a random direction; no jump is generated when the number is above that frequency. When a jump occurs its size is the mean size of the historical jump returns plus a normally distributed random amount with standard deviation σ_J. Notice as well that the proposed modelling approach allows for the possibility of both positive and negative jumps to occur[8].

[8] Merton (1976) in his original jump diffusion model assumes that the jump size distribution is lognormal, and so jumps can occur in only one direction (positive jumps).

In addition, the model takes into account the fact that most energy prices exhibit a seasonal behaviour that follows an annual cycle. Various methods have been used in the literature for the deterministic seasonal component, from a simple sinusoidal (Pilipovic, 1998) or a constant piece-wise function (Pindyck, 1999; Knittel and Roberts, 2005), to a hybrid of both functions (Lucia and Schwartz, 2002; Bierbrauer et al., 2007). This periodic behaviour is accounted for by fitting a sinusoidal function with a linear trend to the actual prices, as described by f_t. The estimation is done using Maximum Likelihood (ML), with the sine term capturing the main annual cycle, and the time trend capturing the long-run growth in prices[9]. Moreover, the possibility for the returns to have a different mean reversion rate after a jump occurs is incorporated into the model. This approach is in line with Nomikos and Soldatos (2008) who use two different coefficients of mean reversion, one for the normal small shocks and another, larger, for the spikes to capture the fast decay rate of jumps observed in the energy markets. Geman and Roncoroni (2006) also analyse the existence of different speeds of mean reversion in the context of mean-reverting jump-diffusion models, by introducing a class of discontinuous processes exhibiting a "jump-reversion" component to represent the sharp upward moves that are shortly followed by drops of the same magnitude. The proposed approach is flexible enough to accommodate the fact that the abnormal events that cause the jumps have different effect in each market and hence, prices tend to remain at the level to which they jump for a longer or shorter period of time, depending on the energy market under investigation. Therefore, prices following a jump are adjusted by using in equation (3.4) a different mean reversion rate, noted as a_{JD}, for a period of time equal to the half-life of jump returns for each energy market; when another jump occurs within the duration of the half-life period used, then a_{JD} is used again for the same number of days, counting from the day following the last jump [see equation (3.4.1)]. If no other jump occurs within that period, then a_2 is used until a new jump occurs. The proposed model, by incorporating this half-life measure, allows for the model to better adapt to the duration of both short- and long-term shocks of a wide magnitude range, exhibited in energy prices. The latter allows for a higher flexibility compared to the model proposed by Nomikos and Soldatos (2008) which fits best mainly the highly volatile electricity markets, as the speed of mean reversion estimated after a spike shock is significantly higher than the normal mean reversion rate. In addition, the

[9] The approach used in Pilipovic (1998) is followed to calculate the seasonal component in the data, because this method is more flexible than using dummy variables. According to Lucia and Schwartz (2002) the use of dummy variables does not provide a smooth function for the seasonal component observed in the data, which can cause discontinuities when pricing forward and futures contracts.

model proposed in this thesis incorporates in its specification GARCH and EGARCH volatility, to account for volatility clustering and any asymmetries that are usually present in energy prices.

Regarding the mean-reverting part of equation 3.4, an exact discretization is used for the simulations since the presence of jumps complicates the use of a large Δt. This is because the drift of the mean-reverting process is a function of the current value of a random variable and in order to simulate the jumps correctly the time step Δt must be small relative to the jump frequency. Because the rare large jumps are of biggest interest, if the time interval Δt is sufficiently small, the probability of two jumps occurring is negligible $\left((\phi\Delta t)^2 \ll \phi\Delta t\right)$. That makes it valid to assume that there can be only one jump for each time interval; in this case one every day since Δt is equal to one day. Especially when Δt is increased to one week or one month, as it is usually the case with real option applications that involve pricing medium- and long-term options, it is more important to use an exact discretization for the simulation process, because the overall error from the first-order Euler and the Milstein approximations will be much higher [10]. The random number generation of the Monte Carlo (MC) simulations already introduces an error in the results, therefore using these approximations that need a very small Δt and thus also introduce a discretization error, would lead to higher computational cost into the simulations.

As for the two time-varying volatility model specifications of equation (3.4.2), in the case of the GARCH process, ε_{t-1}^2 represents the previous periods' return innovations and σ_{t-1}^2 is the last period's forecast variance (GARCH term). As for the EGARCH process, β_0 denotes the mean of the volatility equation. The coefficients β_1 and β_2 measure the response of conditional volatility to the magnitude and the sign of the lagged standardised return innovations, respectively; as such, these coefficients measure the asymmetric response of the conditional variance to the lagged return innovations. When $\beta_2 = 0$, there is no asymmetric effect of the past shocks on the current variance, while when $\beta_2 \neq 0$ asymmetric effects are present in response to a shock; for instance, $\beta_2 > 0$ indicates the presence of an "inverse

[10] Clewlow and Strickland (2000) use the first-order Euler's approximation in order to get the discrete time version of the Arithmetic Ornstein-Uhlenbeck: $x_t = x_{t-1} + a*(\bar{x} - x_{t-1})*\Delta t + \sigma*\sqrt{\Delta t}*\varepsilon_t$ where the discretization is only correct in the limit of the time step tends to zero.

leverage" effect. Finally, β_3 measures the degree of volatility persistence. Knittel and Roberts (2005) suggest that a positive shock in electricity prices represents an unexpected demand shock which has a greater impact on prices relative to a negative shock of the same size, as a result of convex marginal costs and the competitive nature of the market. Moreover, Kanamura (2009) suggests that this inverse leverage effect, i.e. positive correlation between prices and volatility, is a phenomenon often observed in energy markets, whereas evidence from the stock markets suggests that the opposite relationship exists between volatility and prices, namely the "leverage" effect[11]. Hence, intuitively, the asymmetry parameter is expected to be positive and significant for most energy markets, implying that positive shocks have greater effect on the variance of the log-returns compared to negative shocks, consistent with the presence of an "inverse leverage" effect.

Finally, the different models used for modelling the spot prices of the energy markets and the SEI are summarized in table 3-1; "GBM" stands for Geometric Brownian Motion; "MR" for Mean Reversion; "MRJD" for Mean Reversion Jump Diffusion; "OLS" for Ordinary Least Squares (constant volatility).

Table 3-1: Empirical models of energy prices

"GBM" stands for Geometric Brownian Motion; "MR" for Mean Reversion; "MRJD" for Mean Reversion Jump Diffusion, "OLS" for Ordinary Least Squares (constant volatility)

1	GBM
2	MR-OLS
3	MR-GARCH (1,1)
4	MR-EGARCH (1,1)
5	MRJD-OLS
6	MRJD-GARCH (1,1)
7	MRJD-EGARCH (1,1)

3.3. Data

Before discussing the estimation results for the various modelling specifications proposed, first the data used are examined to verify whether the stylized facts aiming at reproducing are indeed present. The behaviour of the spot prices of eight of the most important energy

[11] The "leverage effect" terminology is first used by Black (1976) who suggests that negative shocks on stock prices increase volatility more than positive ones. The intuition behind it is that a lower stock price reduces the value of equity relative to debt, thereby increasing the leverage of the firm and thus making it a more risky investment.

markets that trade futures contracts on NYMEX, and of the constructed spot energy index, is investigated, each one of them having its unique impact on the worldwide marketed energy supply and demand. Because centralized trading lacks for many commodities, the most reliable spot prices are for those that trade active and liquid futures contracts, since these are typically used as a pricing benchmark. In the case of the energy commodities, the NYMEX is the world's largest futures exchange. Spot daily prices from Thomson DataStream are collected, which are the official closing prices of the 1st nearby futures contract issued by the NYMEX, for the period 12/09/2000 to 1/02/2010 for the following contracts and the Spot Energy Index:

1. Heating Oil, New York Harbour No.2 Fuel Oil, quoted in US Dollar Cents/Gallon (US C/Gal); hereafter named as "HO";
2. Crude Oil, West Texas Intermediate (WTI) Spot Cushing, quoted in US Dollars/Barrel (US$/BBL); hereafter named as "WTI";
3. Gasoline, New York Harbour Reformulated Blendstock for Oxygen Blending (RBOB), quoted in US C/Gal; hereafter named as "Gasoline";
4. 1-1 Crack Spread of Gasoline with WTI, quoted in US $/BBL; hereafter named as "CS_Gasoline_WTI"[12];
5. 1-1 Crack Spread of Fuel Oil with WTI, quoted in US $/BBL; hereafter named as "CS_HO_WTI";
6. Natural Gas, Henry Hub, quoted in US Dollars/Milion British Thermal Units (US$/MMBTU); hereafter named as "NG";
7. Propane, Mont Belvieu Texas, quoted in US C/Gal; hereafter named as "Propane";
8. PJM, Interconnection Electricity Firm On Peak Price Index, quoted in US Dollars/Megawatt hour (US $/Mwh); hereafter named as "PJM".
9. Geometric average Spot Energy Index, quoted in index points and constituted by daily prices of WTI, HO, Gasoline, NG, Propane, and PJM; hereafter named as "SEI" [13].

[12] The spot series of the two 1-1 crack spreads with the WTI have been constructed after converting the Fuel Oil and Gasoline spot prices that are quoted in US C/gallon into US $/Barrel, taking into account that there are 42 gallons in one barrel and 100 cents per dollar. Then, the two series are rebased to 100 so they can later be transformed to logarithmic prices and apply our modelling methodology.

[13] The main reason for selecting these energy commodities that trade futures contracts on the NYMEX is that since most energy commodity futures markets are denominated in US dollars, the indexes constituted mostly by local US commodities will have a smaller currency exposure when the commodity is produced and delivered in the US. In the case that the marginal buyer of the underlying commodity is outside the US, then the return to holding that commodity has a large currency exposure. Additional reasons for the commodities' selection are

3.3.1. Spot energy index

All six energy commodities that are included in the spot energy index, as a result of large daily volume trading of standardization qualities, serve as indicators of impeding changes in business activity as they are sensitive to factors affecting both current and future economic conditions. The SEI is constructed as an un-weighted geometric average of the individual commodity ratios of current prices to the base period prices, set at September 12, 2000. Considering that the boom in commodity index investing is a relatively new phenomenon, recent data are utilized to test the proposed investment strategy. The index's construction methodology is similar to that of the world-renowned CRB Spot Commodity Index. The SEI is designed to offer a timely and accurate representation of a long-only investment in energy commodities using a transparent and disciplined calculation.

Geometric averaging provides a broad-based exposure to the six energy commodities, since no single commodity dominates the index. It also helps increase the index diversification by giving even to the smallest commodity within the basket a reasonably significant weight. Gordon (2006) finds that a geometrically weighted index is preferred to alternative weighting schemes, because the daily rebalancing allows the index not to become over- or, under-weighted. This avoids the risks that other types of indexes are subject to, like potential errors in data sources for production, consumption, liquidity, or other errors that could affect the component weights of the index. Furthermore, through geometric averaging the SEI is continuously rebalanced which means that the index constantly decreases (increases) its exposure to the commodity markets that gain (decline) in value, thus avoiding the domination of extreme price movements of individual commodities. As Erb and Harvey (2006) point out, the indexes that rebalance annually eventually become trend followers because commodity prices movements constantly change the weightings, whereas those that rebalance daily stay closer to the original intent of the index. In addition, Nathan (2004) shows that the indexes that use geometric rebalancing, and thus rebalance their weightings daily, generally exhibit lower volatility.

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the following: 1) Quality standardization so that uniform price quotations can be obtained, 2) High trading volume in an open market, 3) Sensitivity to changing market conditions.

The mathematical expression used to calculate the geometric average Spot Energy Index (SEI) is the following:

$$\mathrm{SEI}_t = \left(\prod_{i=1}^{n} \frac{P_t^n}{P_0^n} \right)^{\frac{1}{n}} \times 100 = \sqrt[n]{\frac{P_t^1}{P_0^1} \times \frac{P_t^2}{P_0^2} \times \ldots \frac{P_t^n}{P_0^n}} \times 100, \ \mathrm{n} = 1,2,..6. \tag{3.5}$$

where, SEI_t is the index for any given day, n represents each one of the six commodities comprising the index, P_t^n is the price of each commodity for any given day, and P_0^n is the average (geometric) price of each commodity in the base period.

The SEI provides a stable benchmark so that end-users can be confident that historical performance data is based on a structure that resembles both the current and future composition of the index; thus making SEI suitable for institutional investment strategies. The stable composition of the index is an important element, because when the composition of an index changes over time, the average return of the index does not equal the return of the average index constituent, especially when indexes are equally weighted. The latter makes historical index performance a bad proxy to prospective index returns, thus distorting the information that investors seek (Erb and Harvey, 2006). Moreover, it is a better means for evaluating the movement in energy commodity prices because it is based on spot prices and not on highly volatile prices for future delivery which are subject to contango and backwardation. The SEI is the best indicator of the activity and the trend prevailing in the energy markets, and thus by default provides a gauge of world growth and any potential inflationary pressures. Both private and institutional investors can use the SEI to track its performance, or as a benchmark for actively or passively managed portfolios. In addition, there could be numerous other ways to invest in the SEI such as OTC swaps, structured notes or products offered by third-party asset managers that provide energy commodity exposure benchmarked on the index.

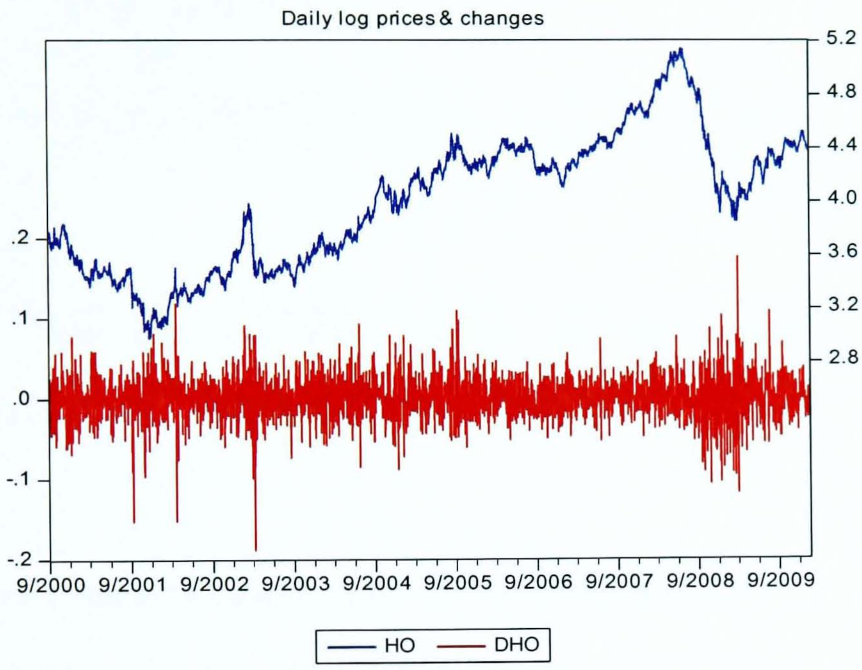
3.3.2. Description and Properties of the Data

The proposed modelling approach for the energy prices and the SEI, as described in the previous section, is a convenient tool for narrating the most important dynamics observed in the actual history of the respective spot prices. All the commodity prices chosen and the constructed spot energy index represent a barometer of the energy market trends worldwide. Figure 3-1 (Panels A to I) shows the evolution of the logarithmic price series and their returns, over the whole period examined from 12/09/2000 to 1/02/2010. It is observed that all series exhibit a distinct upward trend, which is more obvious for the WTI, Gasoline, Heating oil, and the SEI reflecting the continuous rally in commodity prices until the end of June 2008, when WTI reached $145/barrel. Then, a steep downward slope follows until the end of December of the same year, when WTI fell to $31/barrel, with the remainder of the sample showing a small re-bounce with WTI prices recovering and staying at the range of $70 - $80/barrel. A rigid supply, in combination with an expanding global demand for crude oil and its by-products resulted in big demand-supply imbalances, which in turn led to the great variability observed in energy prices. In general, from the figure it can be inferred that all spot energy prices are quite volatile, with the two crack spreads with WTI, the Natural Gas and the PJM markets exhibiting more distinct price jumps. Furthermore, all series vary with time as can be observed by the log-price differences, also forming clusters, both signs that indicate the presence of time-varying volatility.

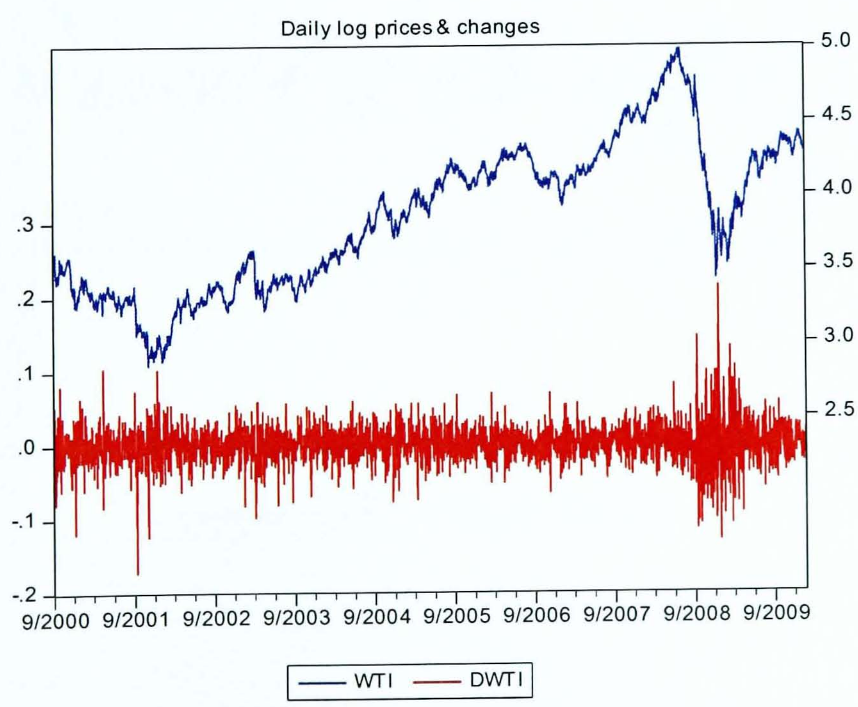
Figure 3-1: Graphs of daily log-spot energy prices and their first log-differences.

This figure shows the daily log-spot and first log-differences for the crude oil, gasoline oil, and heating oil (WTI, Gasoline, HO), the two 1-1 crack spreads with the crude oil (CS_Gasoline_WTI, CS_HO_WTI), the electricity, natural gas, and propane markets (PJM, NG, Propane), and for the spot energy index (SEI). Data period is from 12/09/2000 to 1/02/2010.

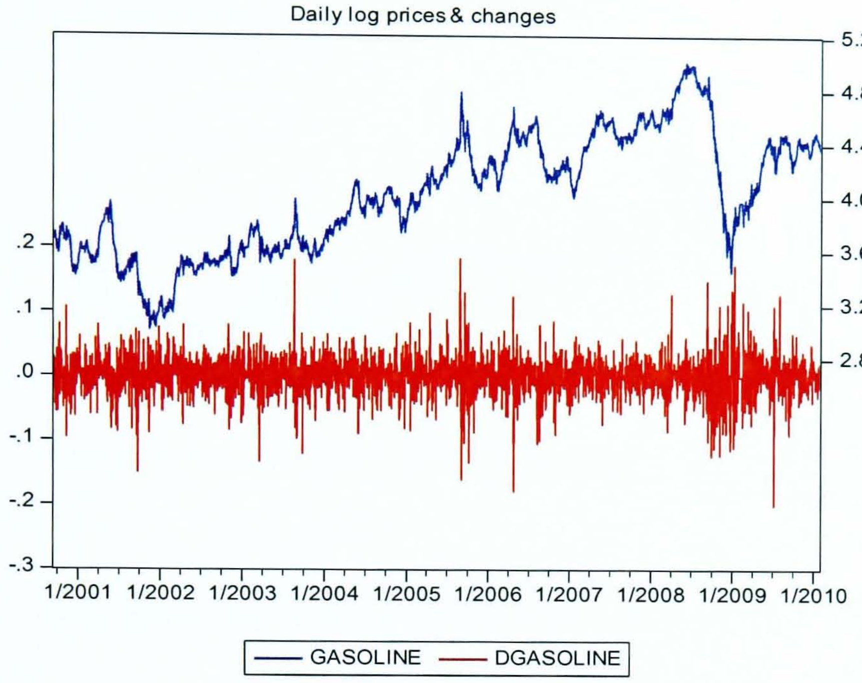
Panel A: Heating Oil - New York Harbour No.2 Fuel Oil (HO)



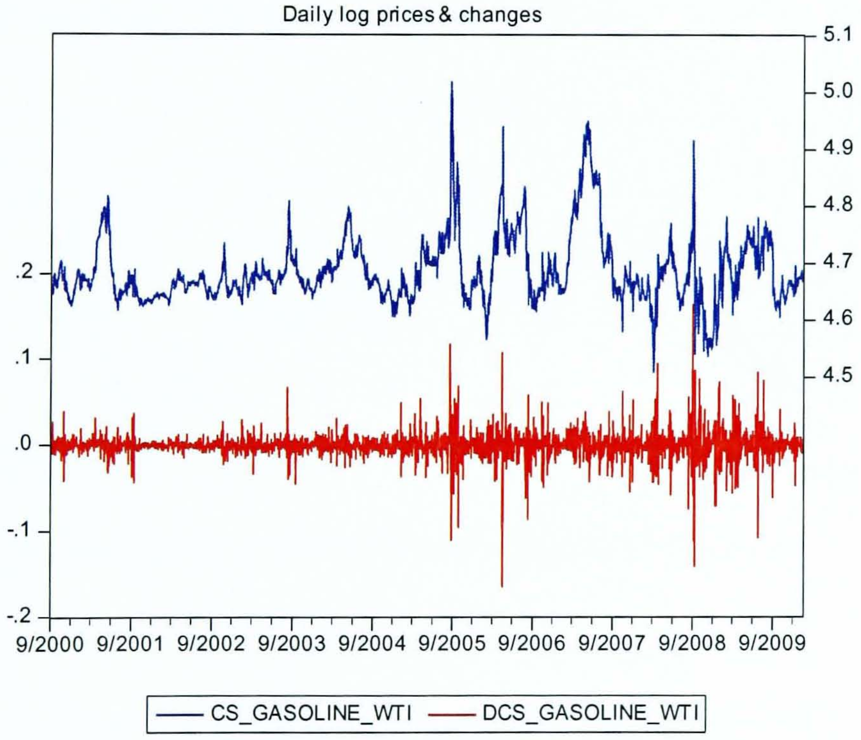
Panel B: Crude Oil – West Texas Intermediate (WTI)



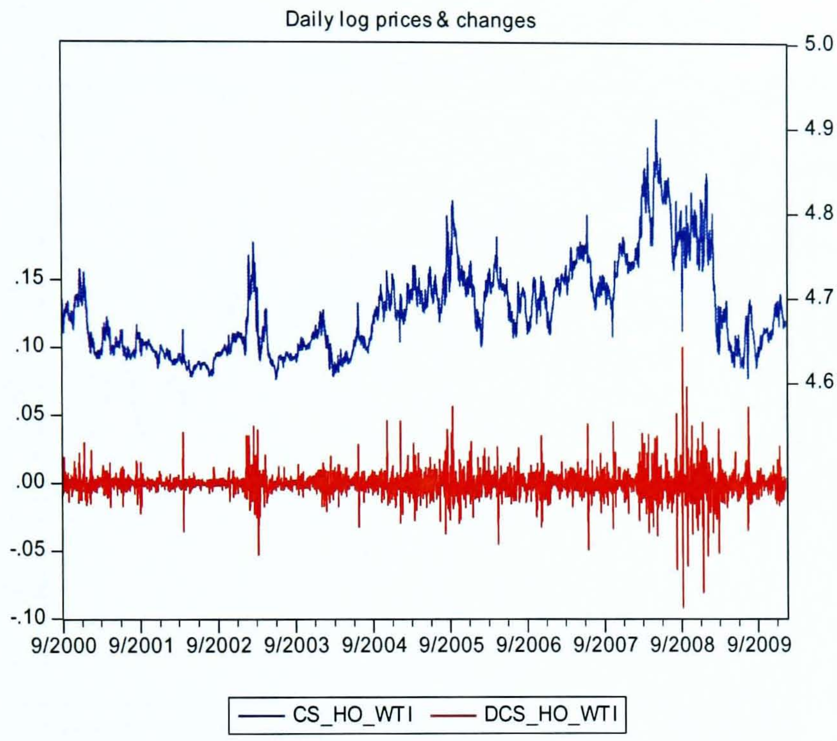
Panel C: Gasoline Oil - New York Harbour RBOB (Gasoline)



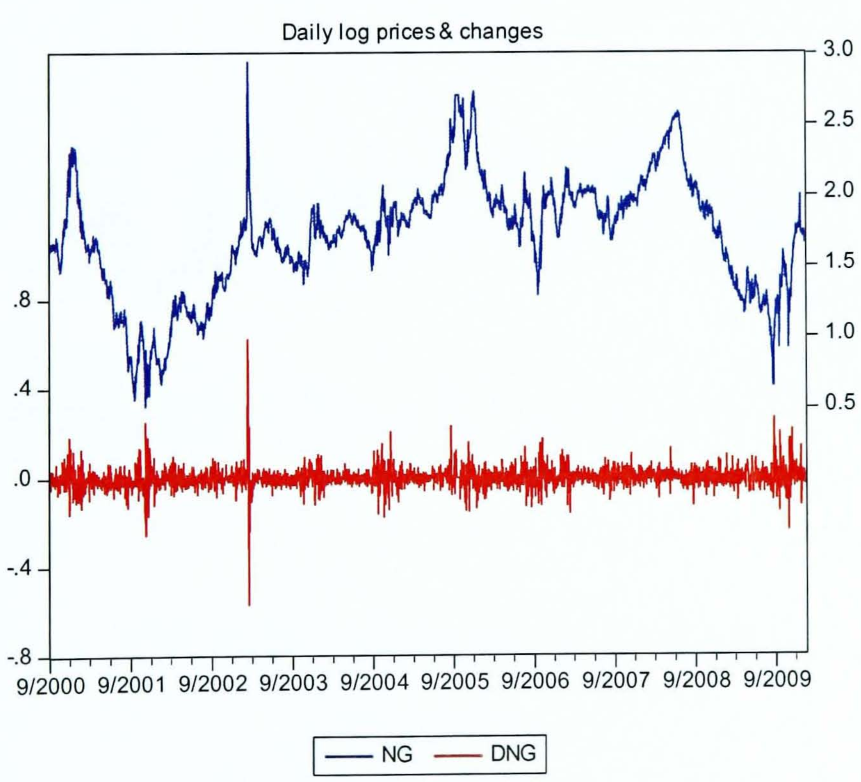
Panel D: 1-1 Crack Spread of Gasoline with WTI (CS-Gasoline-WTI)



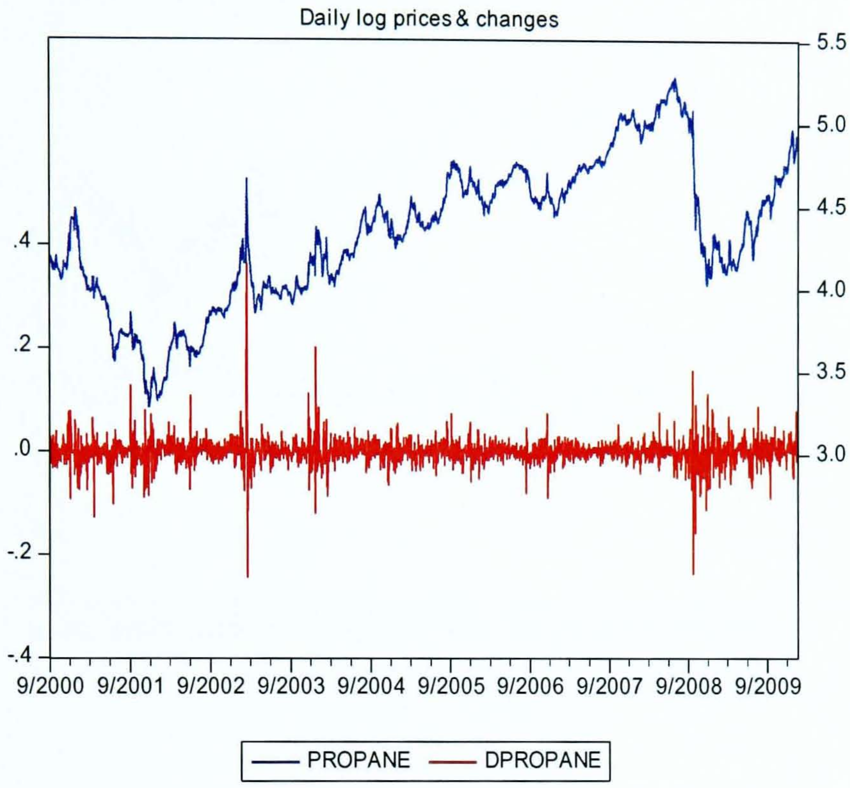
Panel E: 1-1 Crack Spread of Heating Oil with WTI (CS-HO-WTI)



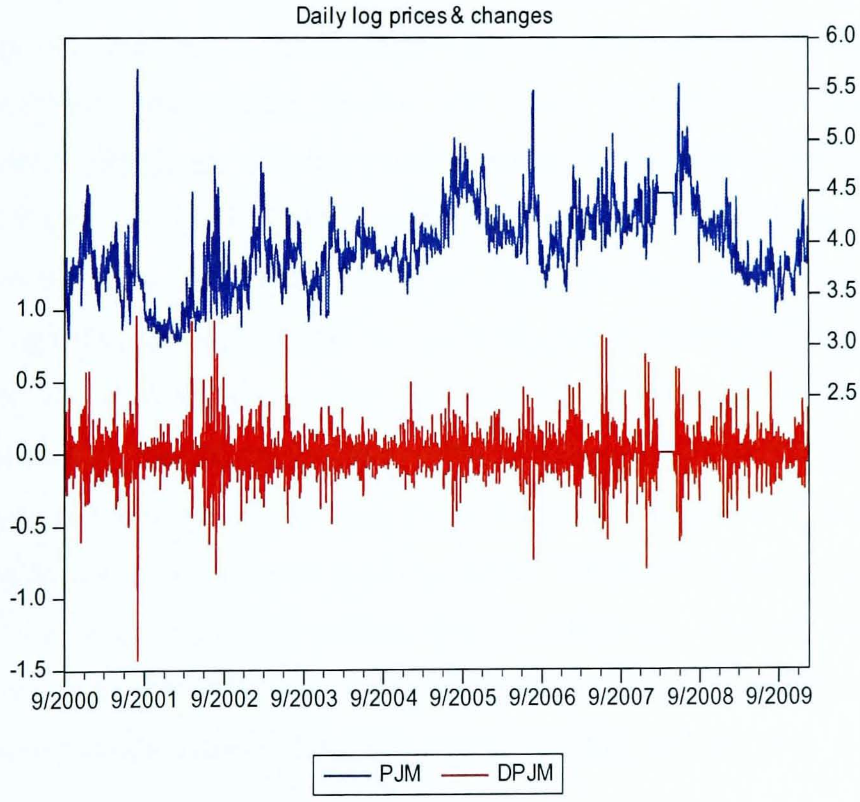
Panel F: Natural Gas - Henry Hub (NG)



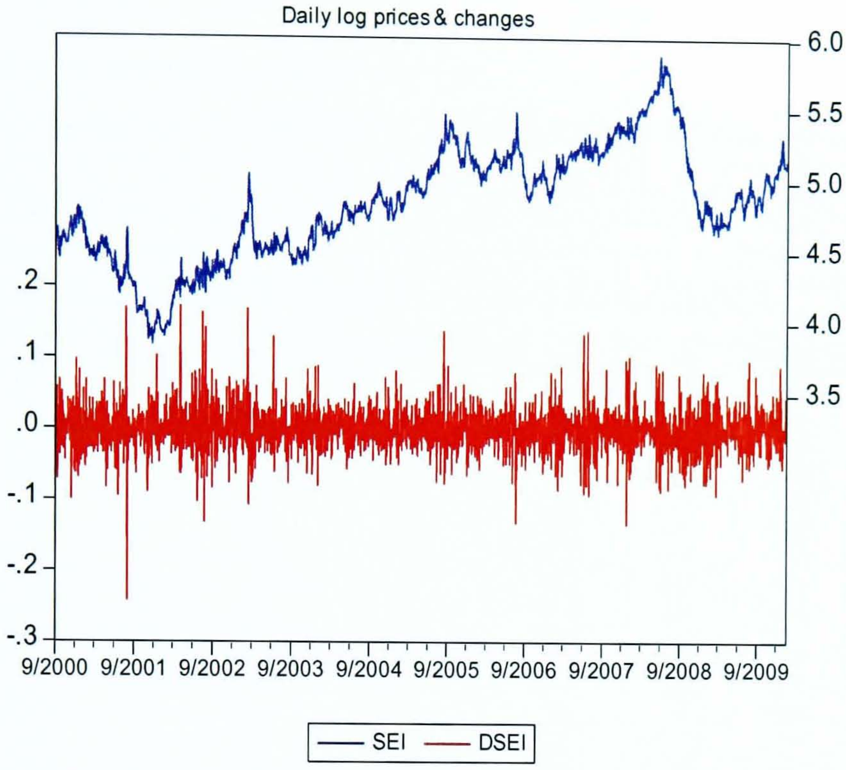
Panel G: Propane - Mont Belvieu Texas (Propane)



Panel H: Interconnection Electricity Firm On Peak Price Index (PJM)



Panel I: Spot Energy Index (SEI)



Next, the descriptive statistics for the natural logarithm of the spot prices of all series are also estimated. To identify whether the series are mean reverting, a comparison procedure known as "confirmatory data analysis" is performed, where two tests for unit root non-stationarity, the Augmented Dickey-Fuller (ADF; Dickey and Fuller, 1979) and the Philips-Perron (PP; Phillips and Perron, 1988), and one test for stationarity, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS; Kwiatkowski et al., 1992), are employed. For the results to be robust, all three tests should give the same conclusion. Table 3-2 shows the descriptive statistics of the spot price series in logarithmic levels (Panel A) and their first differences (Panel B). As can be seen in panel B, the annualized volatility (as measured by the standard deviation of log-returns) of most energy markets ranges from 16% for the Heating Oil – WTI crack spread to 236% for PJM, which is significantly larger than the typical volatility observed in financial markets (e.g. the historical annualised volatility for the S&P500 is in the range of 20%-25%). As for the SEI, being an index, by construction its annualised volatility (48.5%) is in the same range as for the remaining fuel markets, WTI (41.9%), HO (42.4%), and Gasoline (50.5%), and significantly smaller than the highly volatile NG (75.4%). Overall, the two crack spreads have lower volatility than the outright series due to the high correlation between the prices of their constituent contracts.

Table 3-2: Descriptive statistics of energy markets.

Descriptive statistics and the properties of the logarithmic spot prices and their first differences (returns) are presented in Panels A and B, respectively. *, **, *** denote significance at the 10%, 5% and 1% significance level, respectively. Two tests for unit root non-stationarity, the Augmented Dickey-Fuller (ADF; Dickey and Fuller, 1979) and the Philips-Perron (PP; Phillips and Perron, 1988), and one test for stationarity, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS; Kwiatkowski et. al, 1992), are employed. The Jarque-Bera (1980) test for normality on the logarithmic differences is X^2 distributed with 2 degrees of freedom. Q(k) is the Ljung-Box (1978) Q-statistic test for kth order autocorrelation. The Q2(k)-statistic is the Engle's (1982) ARCH test. Both tests are X^2 distributed with k degrees of freedom. Daily data from 12/9/2000 to 1/02/2010.

Panel A: Logarithmic levels

	WTI	HO	GASOLINE	CS_GASOLINE_WTI	CS_HO_WTI	NG	PROPANE	PJM	SEI
Mean Spot Level (S)	\$47.26	\$54.71	\$55.86	\$108.52	\$108.50	\$5.55	\$76.58	\$52.30	\$126.67
Mean (μ)	3.8556	4.0020	4.0229	4.6869	4.6868	1.7146	4.3383	3.9570	4.8416
Mean (excl. jumps)	3.8557	4.0019	4.0231	4.6867	4.6866	1.7139	4.3382	3.9554	4.8411
Median	3.8995	4.0884	4.0304	4.6717	4.6784	1.7630	4.3663	3.9464	4.8482
Maximum	4.9813	5.1434	5.0167	5.0188	4.9116	2.9444	5.2880	5.7014	5.8930
Minimum	2.8611	2.9807	3.0108	4.5096	4.6040	0.5277	3.2865	3.0022	3.8440
Standard Deviation	0.4782	0.4909	0.4489	0.0604	0.0551	0.4087	0.4353	0.4025	0.4066
Skewness	0.1159	0.0612	0.0228	1.4175	0.8940	-0.2736	-0.1075	0.2077	-0.0550
Kurtosis	2.0980	2.1135	2.1056	6.3502	3.4028	3.0529	2.3948	3.1987	2.5371
Jarque-Berra	88.5425	81.7510	81.8749	1966.2720	342.9089	30.8473	42.1055	21.6362	23.1069
KPSS	4.798	4.789	4.529	0.331	2.729	1.491	4.014	2.248	4.041
ADF	-1.281	-1.156	-1.735	-5.881***	-3.891***	-2.546	-1.130	-5.372***	-1.437
	(0.640)	(0.695)	(0.414)	(0.000)	(0.002)	(0.105)	(0.706)	(0.000)	(0.566)
PP	-1.189	-1.140	-1.647	-5.960***	-3.604***	-2.740	-1.205	-8.938***	-1.548
	(0.681)	(0.702)	(0.459)	(0.000)	(0.006)	(0.068)	(0.675)	(0.000)	(0.509)

Panel B: Logarithmic differences (returns)

	WTI	HO	GASOLINE	CS_GASOLINE_WTI	CS_HO_WTI	NG	PROPANE	PJM	SEI
Mean	0.0003	0.0003	0.0003	0.0000	0.0000	0.0000	0.0003	0.0002	0.0002
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.2128	0.1758	0.1825	0.1647	0.1011	0.6227	0.3634	0.9626	0.1721
Minimum	-0.1722	-0.1883	-0.2004	-0.1648	-0.0918	-0.5695	-0.2439	-1.4283	-0.2423
Standard Deviation	0.0264	0.0267	0.0318	0.0159	0.0101	0.0475	0.0248	0.1490	0.0306
Annualised Volatility	0.419	0.424	0.505	0.252	0.161	0.754	0.393	2.365	0.485
Skewness	0.0056	-0.1387	-0.1503	-0.2790	0.0988	0.6929	0.6235	0.0709	0.1974
Kurtosis	8.1283	6.7592	7.1613	23.7001	17.5338	29.1982	34.5256	12.0735	7.5062
Jarque-Berra	2683.6330	1449.8570	1776.2050	43756.1000	21558.2300	70231.8700	101574.2000	8402.9070	2087.9340
KPSS	0.070	0.093	0.043	0.013	0.046	0.037	0.086	0.045	0.061
ADF	-51.226***	-53.796***	-51.630***	-55.570***	-58.124***	-40.500***	-32.619***	-25.179***	-23.941***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PP	-51.354***	-53.847***	-51.683***	-58.078***	-67.410***	-47.704***	-50.167***	-106.526***	-44.625***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q (1)	3.038*	17.173***	4.543*	33.003***	62.716***	3.967**	0.443	8.524***	31.920***
Q (20)	40.948***	36.642***	28.034	60.190***	120.560***	129.360***	58.807***	234.090***	126.170***
Q^2 (1)	38.189***	69.081***	55.543***	142.890***	356.970***	563.340***	439.440***	14.912***	21.573***
Q^2 (20)	1105.700***	322.230***	330.990***	517.730***	720.610***	1206.900***	512.560***	259.280***	173.770***

Looking at panel A of Table 3-2, is observed that for all energy markets, with the exception of NG, Propane, and the SEI, the skewness is positive, indicating that extreme high values are more probable than low ones. Turning next to the log-price changes, the results regarding the coefficients of skewness are different since only the Heating Oil, Gasoline, and the crack spread of WTI with Gasoline are negatively skewed, whereas the rest of the energy markets are positively skewed (see panel B, table 3-2). Also looking again in Panel B of table 3-2, the coefficient of kurtosis which gives an indication of the probability of extreme values, is above three for all energy markets, implying that log-returns are leptokurtic; this suggests that the probability of extremely high or low returns is much higher than that assumed by the normal distribution. This effect is more obvious for the PJM, NG, the two crack spreads, and Propane in which case the high values of the coefficient of kurtosis (between 12.07 and 34.53) is indicative of spikes in the price series. It is also found that normality is overwhelmingly rejected in the first difference series for all the energy markets and the SEI, on the basis of the Jarque-Bera (1980) test which is significant at the 1% level. It is obvious that non-normality occurs mostly due to the large price movements and spikes in all logarithmic price series that eventually lead to fat tails.

Moreover, from panel A in table 3-2 it is observed that the average logarithmic price for most energy markets is reduced when the filtered series is examined (i.e. when jumps are excluded) indicating that jumps have a positive impact on log-prices[14]. The only exceptions are the WTI and Gasoline markets where jumps have a negative impact on log-prices. It can also be inferred that the price-levels of most energy markets are not stationary, a conclusion confirmed by all three tests; the only exceptions are, as expected, the two crack-spreads and the PJM markets where price levels appear to be stationary on the basis of the ADF and PP tests. On the other hand, from Panel B of table 3-2 it can be seen that the first differences of the spot log-price series are strongly stationary for all energy markets, indicating the presence of mean reversion in the series. This conclusion, although it may not have been expected due to the presence of jumps in most of the energy series, can be justified by the fact that these jumps do not seem to affect the stationarity of the series because they are short-lived and price levels eventually revert to their mean after a jump has occurred. Panel B also reports the Ljung-Box (1978) $Q(k)$-statistic and Engle's (1982) ARCH test ($Q^2(k)$-statistic) to test the significance of autocorrelation in the returns and squared returns for lags one and 20, respectively. From the reported values there is evidence of serial correlation for all the log-return series, and for both time lags, at conventional significance levels; the only exception is for the Gasoline market for 20 lags. Finally, based on Engle's ARCH test significant serial correlation in the squared log-returns of all energy markets and the SEI is found, which indicates the presence of time-varying volatility in the return series.

[14] A detailed discussion on how the filtered series is estimated is given in the following section.

3.4. Empirical findings

From the total sample of 2,450 daily observations, for the purposes of this chapter's analysis only the first 1,827 observations are used, representing the period 12/09/2000 to 12/09/2007. The input parameters for the Monte Carlo simulations are estimated from the historical spot price series of the different commodities. First the jump parameters are considered. Estimating the jump parameters, especially for energy prices, can be quite complicated because usually there is no indication of the exact time the jump will occur, and thus jumps can only be observed as part of the historical spot time series. There are two widely used approaches for estimating the jump parameters, the first being the Recursive Filter (R-F) (Clewlow and Strickland, 2000; Clewlow et al. 2000b), and the second being the Maximum Likelihood (M-L) (Ball and Torous, 1983). Empirical analysis suggests that the R-F estimation method can be superior to the M-L method when it comes to estimating jump parameters in energy markets; this is because the former method can pick the lower frequency, higher volatility jump components, instead of the higher frequency, lower volatility jumps that are estimated better with the latter. According to Clewlow and Strickland (2000), a potentially undesirable property of the M-L method is that it tends to converge on the smallest and most frequent jump components of the actual data. As energy price return series exhibit jumps that range from very high frequency and low volatility to low frequency and high volatility, it is important to be able to efficiently capture the latter ones.

Therefore, given that jumps in the energy markets are relatively infrequent but of large magnitude, the R-F method is considered to be more appropriate. Correct identification and measurement of jumps is very important. For instance, Nomikos and Soldatos (2008) point out the importance of spikes in electricity prices especially for market suppliers because, although their costs depend on the variable price for electricity, their revenues are mainly fixed; in fact, these rare spikes are the most important motive for hedging in the energy markets. In addition, these rare but large returns, significantly affect the value of medium- and long-term energy real investments, as is the case for example when pricing an undeveloped oil field. In particular, according to Dias (2003), the two main sources of uncertainty in an oilfield development project are fluctuations in the oil prices (market uncertainty), and variations in the volume and quality of the reserves (technical uncertainty). A mean-reverting model with jumps can capture both the mean-reverting price evolution of the underlying resources, as well as the sudden changes in prices due to unexpected news in the market.

The R-F algorithm is then implemented as follows: By assuming that jumps are relatively infrequent and that the diffusive volatility can be estimated based on the sample standard deviation of returns, those "extreme" returns that are more than three standard deviations away from the mean are identified as jumps, consistent with most studies in the literature. Now, given that some of the returns have been identified as jumps, a new estimate of the diffusive volatility is calculated by recalculating the sample standard deviation of returns, after filtering out those returns previously identified as jumps. During the filtering process, when a jump is identified, its respective log-price is being removed from the series and then replaced by the average of the previous and the next log-price. Then the new returns are calculated based on the filtered series. The new calculation gives a lower estimate of the diffusive volatility and, based on that lower volatility, the same procedure is repeated in order to identify new jump returns. The process is continuously repeated until the estimates converge and no further jumps can be identified. Finally, the jump parameters necessary for calibrating the models are calculated, on an annual basis, from the following relationships:

ϕ = Number of jump returns/ Time period of the data

$\bar{\kappa}_J$ = Average jump size of returns

σ_J = Standard deviation of jump returns

Panel A of table 3-3 presents the estimated jump parameters used in the MRJD models, as calculated by the Recursive Filter algorithm; these parameters include the jumps' daily frequency (Φ), daily standard deviation (σ_J) and average jump size ($\bar{\kappa}_J$). It can be seen that the average size of the jump returns is negative for the WTI, Gasoline, and PJM markets, whereas for the rest energy markets and the SEI it is positive. As for the daily jump frequencies, the highest frequency is observed for the crack spread of WTI with Gasoline, followed by the other volatile markets, i.e. the gas and electricity markets. Finally, in terms of the jumps' volatility, the highest daily standard deviation values are calculated for the Gasoline (10.78%), Natural Gas (16.14%) and PJM (51.94%) markets, and the SEI (11.16%) which are also the markets with the highest unconditional volatilities as evidenced in table 3-2.

Moreover, for comparison reasons, the parameters of the jump returns for all energy markets were also calculated using the Maximum Likelihood Estimation method, and the results are presented in table 3-4. The results verify the initial intuition for using the R-F method instead of the M-L method for estimating the jump parameters, as the volatility of all returns identified as jumps is smaller under the M-L, since the R-F method is able to capture the larger in size jumps, which lead to a smaller standard deviation of the jump returns series in all cases; the only exception is in the case of the CS-Gasoline-WTI series. In addition, when the mean jump size between the two methods is compared in absolute terms, it is found that in all cases the average jump size detected by the M-L method is smaller than the average jump size detected with the R-F method; the only exception is for the Gasoline and PJM markets. Also, an opposite sign regarding the direction of the average jump returns is observed only in the case of the CS-Gasoline-WTI, Propane, and PJM markets. It is also observed that the daily frequency of the jumps detected with the M-L method in the case of HO, CS-HO-WTI, and PJM markets is significantly larger than the daily frequency estimated with the R-F method. Another case where the M-L method provides a higher daily frequency than the RF method is in the SEI series. The last two observations strengthen even further the initial decision to use the R-F method instead of the M-L, as the undesirable property of the latter that it tends to converge on the smallest and most frequent jump components of the actual data can be avoided. It is the low frequency but high volatility jumps that need to be efficiently captured in the case of energy price returns. As for WTI, Gasoline, NG and Propane, the differences between the two methods are negligible, with the R-F estimates being slightly higher than the M-L estimates; the only significant difference occurs in the case of the CS-Gasoline-WTI series.

Table 3-3: Estimated jump parameters, mean reversion rates, volatility, and half-lives.

The filtered series exclude all returns that have been identified as jumps (more than three times the standard deviation of the smooth returns). Φ is the daily frequency of a jump occurring, σ_J is the daily standard deviation of jump returns, and $\bar{\kappa}_J$ the average size of jump returns. The diffusive mean reversion rate α, is estimated using eq. (3.7) after running the regression of eq. (3.6). The mean reversion rate used after a jump has occurred α_{JD}, for a period of time equal to the half-life of jump returns, is estimated using eq. (3.10) after running the regression of eq. (3.9). Also, σ is the daily standard deviation of log-price differences, as estimated from eq. (3.8) for the un-filtered and filtered series, respectively. All estimates for the half-lives of both the smooth and jumpy returns are calculated using eq. (3.11). The half-lives of the jumpy returns, in days, are the respective durations we are using in our MRJD models for the higher mean reversion rate (α_{JD}) after a jump occurs.

Panel A: Jump parameters used in the MRJD models

	Φ_{daily}	σ_J	$\bar{\kappa}_J$
WTI	0.0192	0.0725	-0.0460
HO	0.0159	0.0899	0.0086
GASOLINE	0.0235	0.1078	-0.0089
CS_GASOLINE_WTI	0.1873	0.0305	0.0208
CS_HO_WTI	0.0405	0.0277	0.0065
NG	0.0581	0.1614	0.0627
PROPANE	0.0476	0.0816	0.0176
PJM	0.0728	0.5194	-0.0214
SEI	0.0318	0.1116	0.0385

Panel B: Mean reversion rates, daily st. deviations, and half-lives of smooth and jumpy returns

	Un-filtered series (MR)	Filtered Series (MRJD)	Half-lives for MRJD models, in days
WTI			
α	0.001	0.001	998
α_{JD}	-	0.019	36
σ	0.023	0.022	
HO			
α	0.001	0.001	771
α_{JD}	-	0.010	67
σ	0.026	0.024	
GASOLINE			
α	0.002	0.002	362
α_{JD}	-	0.021	34
σ	0.030	0.027	
CS_GASOLINE_WTI			
α	0.023	0.012	60
α_{JD}	-	0.026	26
σ	0.013	0.009	
CS_HO_WTI			
α	0.020	0.013	55
α_{JD}	-	0.041	17
σ	0.008	0.007	
NG			
α	0.007	0.004	155
α_{JD}	-	0.010	72
σ	0.049	0.038	
PROPANE			
α	0.001	0.000	2635
α_{JD}	-	0.008	87
σ	0.024	0.017	
PJM			
α	0.075	0.055	13
α_{JD}	-	0.115	6
σ	0.158	0.132	
SEI			
α	0.003	0.003	264
α_{JD}	-	0.007	103
σ	0.031	0.029	

Table 3-4: Estimation of jump parameters using the M-L method.

The M-L method is used to estimate the jump parameters of a Mean-reverting Jump Diffusion process. It is based on the methodology used by Ball and Torrus (1983) and Weron and Misiorek (2008). It is assumed that the arrival rate for two jumps within one period (dt, i.e. one day) is negligible, and that the likelihood function is a product of the densities of a mixture of two normals. Φ is the daily frequency of a jump occurring, σ_J is the daily standard deviation of jump returns, and $\bar{\kappa}_J$ the average size of jump returns.

	Φ_{daily}	σ_J	$\bar{\kappa}_J$
WTI	0.0127	0.0647	-0.0309
HO	0.1235	0.0429	0.0011
GASOLINE	0.0090	0.0987	-0.0337
CS_GASOLINE_WTI	0.0358	0.0420	-0.0027
CS_HO_WTI	0.1841	0.0153	0.0017
NG	0.0360	0.1550	0.0090
PROPANE	0.0441	0.0752	-0.0024
PJM	0.2355	0.2520	0.0379
SEI	0.0356	0.0805	0.0176

In addition, to be able to provide more information on the results of the Recursive Filtering process, the specific date that each jump occurs has been identified. The total number of jumps per quarter has been aggregated and the results are shown in figures 3-2 and 3-3. Looking at figure 3-2, across the three commodities of the fuels complex, i.e. the WTI, HO and Gasoline, there is no correlation pattern in the occurrence of jumps. For example, whenever there is at least one jump for WTI, in most occasions across the seven year period examined there is no contagion effect to the other two markets, HO and Gasoline; that is the case in Q3-2000, Q1-2001, Q2-2003, Q4-2003 and Q1-2006. The same applies for HO in Q2-2002, Q3-2004, and Q2-2007, and for Gasoline in Q2-2004. On the other hand, as expected, high correlation of jump occurrence is identified for Gasoline and HO, and their respective crack spreads with WTI. This correlation effect is highly distinctive for example in Q1-2003 where for HO there are seven jumps detected, and for the respective crack, the CS-HO-WTI, there are 13 jumps detected. A similar case can be depicted for Q3-2005 where there are six jumps detected for Gasoline and 19 jumps for the CS-Gasoline-WTI. Looking at figure 3-3, there is a correlation detected between the NG and Propane jumps, having a tendency to occur more frequently during the winter months. In almost all cases, whenever there are jumps occurring for any of the two markets, there are also jumps reported for the other, with this effect being more profound in Q4-2001, Q1-2003, Q4-2004, and Q4-2005. A similar correlation effect is detected between the PJM and the SEI, however with the number of jumps detected in each quarter being smaller compared to the NG and Propane markets.

Furthermore, jumps across all energy commodities and the SEI do not seem to exhibit any clustering behaviour[15]. Looking at the quarterly aggregates of the jumps, the only clustering effect that can be observed is during the years 2001, 2003, and 2005, which is directly related to specific events that have shaken the world economy and energy markets; in the last two quarters of 2001 the jumps relate mostly with the September 11 terrorist attacks in the US; in the first two quarters of 2003 it is the US invasion to Iraq that has shaken the energy markets; in the last two quarters of 2005 it is the July terrorist attacks in London, and the devastating hurricane Katrina that in August destroyed New Orleans in the US, creating at the same time major disruptions in the supply of energy from the Gulf of Mexico.

To statistically test for the existence of any clustering effect in the occurrence of jumps for each energy market and the SEI, a distributional comparison on the daily data series has been performed with the two-sample Kolmogorov-Smirnov (K-S) test. The K-S test is a non-parametric test for the equality of two probability distributions[16]. In this case, the actual distribution of daily jumps, as identified by the R-F methodology, is compared to the distribution of a series of jumps as generated by a Poisson process, with a frequency equal to the frequency of jump occurrence as reported in panel A of table 3-3 for each energy market and the SEI. The null hypothesis of the K-S test is that the two samples are from the same continuous distribution, at the 5% significance level. The test-statistic numbers for the K-S test are reported in table 3-5, where it can be clearly seen that the null hypothesis cannot be rejected for any of the energy markets or the SEI. The latter finding confirms that there is no clustering behavior observed in the occurrence of jumps for all markets examined.

[15] Especially when looking at the daily observations, there is no apparent clustering effect for any of the energy markets examined and the SEI.
[16] A more detailed explanation of the K-S test is given in section 3.5.

Table 3-5: Distributional comparison with the Kolmogorov-Smirnov test, of the actual daily jumps' series and a Poisson generated series.

Comparison of the actual distribution of daily jumps as identified by the R-F methodology, and the distribution of a series of jumps as generated by a Poisson distribution with a frequency equal to the reported frequency of jump occurrence in panel A of table 3-3, for each energy market and the SEI. The test-statistic numbers are reported for the Kolmogorov-Smirnov (K-S) test. The null hypothesis of the K-S test is that the two samples are from the same continuous distribution, at the 5% significance level.

	K-S
WTI	0.0011
HO	0.0022
GASOLINE	0.0005
CS_GASOLINE_WTI	0.0011
CS_HO_WTI	0.0044
NG	0.0038
PROPANE	0.0006
PJM	0.0033
SEI	0.0011

Furthermore, to test whether there is any seasonal behaviour in the occurrence of jumps, the quarterly data are regressed against quarterly dummies, for the whole period examined, and for all energy markets and the SEI. The results of the coefficients of the dummies for each quarter are reported in table 3-6, along with their respective p-values included in brackets. In case that the coefficient of a quarterly dummy is significant, at the 1% significance level, this would indicate the presence of seasonality in the jump occurrence. However, as it can be seen from the table, none of the energy markets or the SEI exhibits any seasonality during each of the four quarters, for the seven year period examined. In addition, each calendar year has been split into two seasons, a cold season which includes the three months of the fourth quarter of the previous year and the first quarter of the same year, and a warm season that includes all months in the second and third quarters of the same year. Then, for each cold and warm season, the total number of jumps per season has been aggregated in order to check whether the jump occurrence for each energy commodity and the SEI is seasonal or not[17]. The results are presented in figure 3-4. It is observed that the jump occurrence for NG and Propane seems to exhibit some seasonal pattern during the cold season, with the effect being more profound for the latter commodity. There is a large number of jumps observed every

[17] For the same period, besides quarterly data, also six-month jumps' data, representing the cold and warm seasons, were regressed against a seasonal dummy, with the results confirming again that there is no seasonality effect in the occurrence of the jumps for any of the energy markets or the SEI.

cold season, whereas every warm season there seem to be either no jumps at all or very few. This can be attributed to the fact that during the cold season the residential and commercial demand for Propane and NG is higher as they are used for the generation of electricity; with their share continuously increasing lately due to being among the cleanest fuels that can be used for power generation. PJM also seems to exhibit some seasonality in the jump occurrence during the warm season, with the effect being more profound in the years 2001, 2002, and 2007. This is consistent with the expectation that during the warm season demand for electricity is higher due to air-conditioning needs, coupled with any potential overloads of the system which drive prices up and down unexpectedly and at high rates, leading to the occurrence of jumps in the prices.

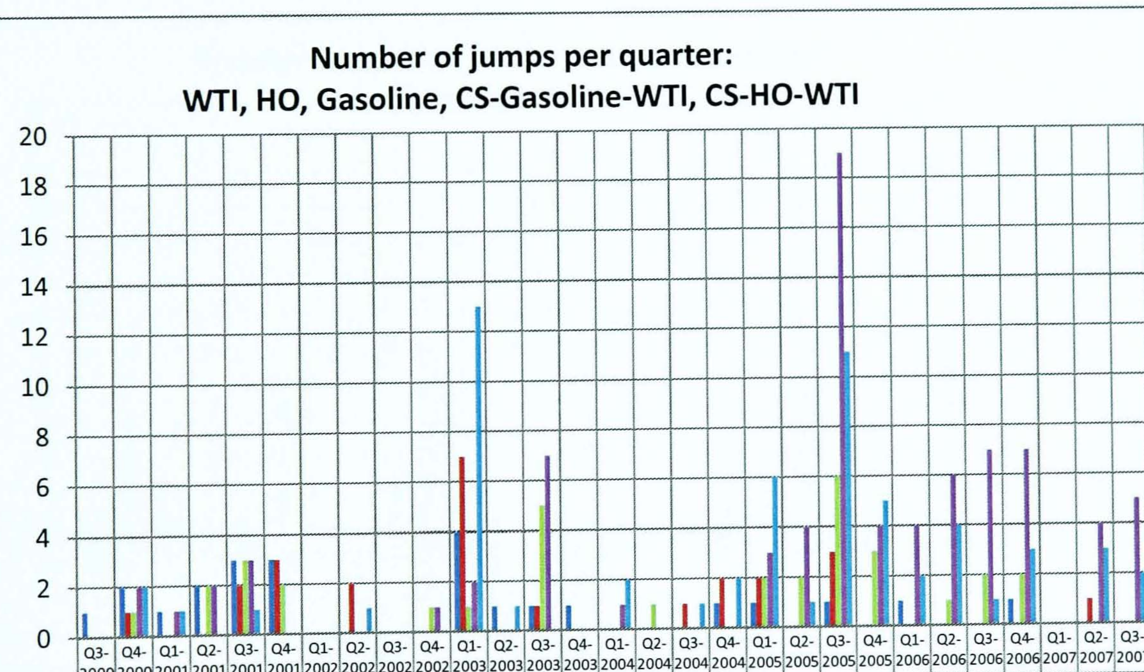
On the other hand, the two crack spreads of Gasoline and HO with WTI seem not to exhibit any seasonality during the cold or warm seasons as they are volatile consistently throughout the seven year period examined, providing a large number of jumps during both seasons. Moreover, the remaining commodities from the fuels complex, i.e. WTI, HO, and Gasoline, seem also not to exhibit any seasonality in terms of jump occurrence either during the cold or warm seasons, as only a small number of jumps is depicted, which is sporadically spread across all seven years. It can be concluded that the occurrence of jumps for the latter three energy commodities is predominately affected by specific events that cause economic turmoil, political events, or coordinated monetary and fiscal policy changes. These events can mute, magnify, or even alter any seasonal cycles. For example, if overall economic conditions worsen (e.g. during a recession), this may suddenly reduce demand, thereby causing limited price gains in periods of seasonal strength. Finally, for the SEI there is also no indication of any seasonal cycle presence in the jump occurrence.

Table 3-6: Regression results of the jumps against quarterly dummies.

The table reports the regression results of the jumps against quarterly dummies, for the whole period examined, and for all energy markets and the SEI. The coefficients of the dummies for each quarter are reported, along with their respective p-values included in brackets. In case that the coefficient of a quarterly dummy is significant, at the 1% significance level, this would indicate the presence of seasonality in the jump occurrence. The regression equation is: $x_t = c + Q1 + Q2 + Q3 + \varepsilon_t$; $\varepsilon_t \sim N(0,\sigma)$, where x is the series of jumps for each energy market and the SEI, Q is the quarterly dummy, and c is a constant which captures the effect of the remaining quarter i.e. Q4.

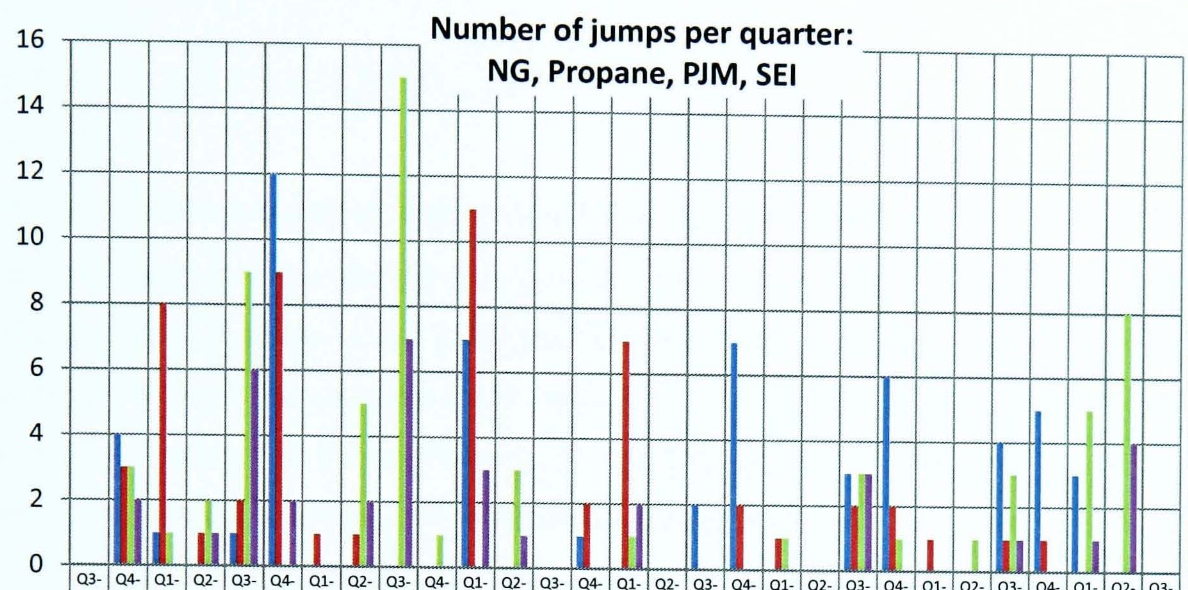
	C		Q1		Q2		Q3	
WTI	1.14286	(0.01074)	-0.14286	(0.80946)	-0.71429	(0.23444)	-0.39286	(0.49525)
HO	0.85714	(0.16510)	0.42857	(0.61758)	-0.42857	(0.61758)	0.01786	(0.98281)
GASOLINE	1.28571	(0.03472)	-0.85714	(0.30251)	-0.42857	(0.60325)	0.71429	(0.37353)
CS_GASOLINE_WTI	2.00000	(0.18347)	-0.42857	(0.83746)	0.28571	(0.89119)	3.12500	(0.13108)
CS_HO_WTI	1.71429	(0.17417)	1.57143	(0.10768)	-1.57143	(0.24916)	-0.32143	(0.80520)
NG	3.42857	(0.01636)	1.57143	(0.10768)	-1.57143	(0.24916)	-0.32143	(0.80520)
PROPANE	2.71429	(0.01199)	1.42857	(0.32290)	-2.42857	(0.09883)	-2.08929	(0.14025)
PJM	0.71429	(0.58341)	0.42857	(0.81556)	2.00000	(0.28178)	3.03571	(0.09696)
SEI	0.57143	(0.42350)	0.28571	(0.77596)	0.57143	(0.57018)	1.55357	(0.11873)

Figure 3-2: Number of jumps detected with the R-F method per quarter, for the whole sample period, for the WTI, HO, Gasoline, CS-Gasoline-WTI, and CS-HO-WTI markets.



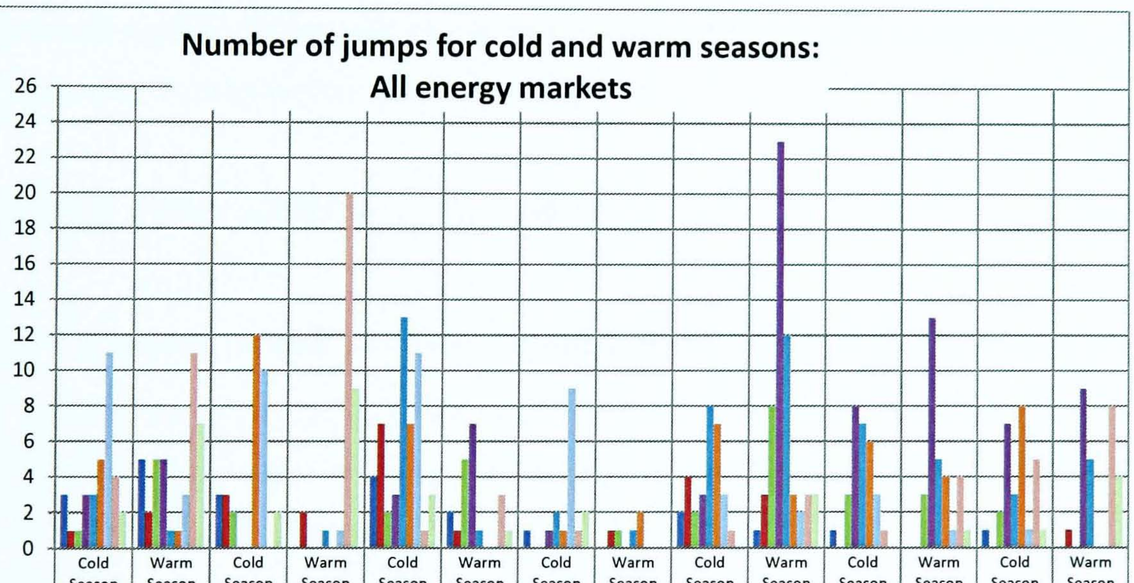
	Q3-2000	Q4-2000	Q1-2001	Q2-2001	Q3-2001	Q4-2001	Q1-2002	Q2-2002	Q3-2002	Q4-2002	Q1-2003	Q2-2003	Q3-2003	Q4-2003	Q1-2004	Q2-2004	Q3-2004	Q4-2004	Q1-2005	Q2-2005	Q3-2005	Q4-2005	Q1-2006	Q2-2006	Q3-2006	Q4-2006	Q1-2007	Q2-2007	Q3-2007
WTI	1	2	1	2	3	3	0	0	0	0	4	1	1	1	0	0	0	1	1	0	1	0	1	0	0	1	0	0	0
HO	0	1	0	0	2	3	0	2	0	0	7	0	1	0	0	0	1	2	2	0	3	0	0	0	0	0	0	1	0
GASOLINE	0	1	0	2	3	2	0	0	0	1	1	0	5	0	0	1	0	0	2	2	6	3	0	1	2	2	0	0	0
CS_GASOLINE_WTI	0	2	1	2	3	0	0	0	0	1	2	0	7	0	1	0	0	0	3	4	19	4	4	6	7	7	0	4	5
CS_HO_WTI	0	2	1	0	1	0	0	1	0	0	13	1	0	0	2	0	1	2	6	1	11	5	2	4	1	3	0	3	2

Figure 3-3: Number of jumps detected with the R-F method per quarter, for the whole sample period, for the NG, Propane, PJM markets and the SEI.



	Q3-2000	Q4-2000	Q1-2001	Q2-2001	Q3-2001	Q4-2001	Q1-2002	Q2-2002	Q3-2002	Q4-2002	Q1-2003	Q2-2003	Q3-2003	Q4-2003	Q1-2004	Q2-2004	Q3-2004	Q4-2004	Q1-2005	Q2-2005	Q3-2005	Q4-2005	Q1-2006	Q2-2006	Q3-2006	Q4-2006	Q1-2007	Q2-2007	Q3-2007
NG	0	4	1	0	1	12	0	0	0	0	7	0	0	1	0	0	2	7	0	0	3	6	0	0	4	5	3	0	0
PROPANE	0	3	8	1	2	9	1	1	0	0	11	0	0	2	7	0	0	2	1	0	2	2	1	0	1	1	0	0	0
PJM	0	3	1	2	9	0	0	5	15	1	0	3	0	0	1	0	0	0	1	0	3	1	0	1	3	0	5	8	0
SEI	0	2	0	1	6	2	0	2	7	0	3	1	0	0	2	0	0	0	0	0	3	0	0	0	1	0	1	4	0

Figure 3-4: Number of jumps detected with the R-F method for the cold and warm seasons, for the whole sample period, for all energy markets and the SEI.



	Cold Season 2000-01	Warm Season 2001	Cold Season 2001-02	Warm Season 2002	Cold Season 2002-03	Warm Season 2003	Cold Season 2003-04	Warm Season 2004	Cold Season 2004-05	Warm Season 2005	Cold Season 2005-06	Warm Season 2006	Cold Season 2006-07	Warm Season 2007
WTI	3	5	3	0	4	2	1	0	2	1	1	0	1	0
HO	1	2	3	2	7	1	0	1	4	3	0	0	0	1
GASOLINE	1	5	2	0	2	5	0	1	2	8	3	3	2	0
CS_GASOLINE_WTI	3	5	0	0	3	7	1	0	3	23	8	13	7	9
CS_HO_WTI	3	1	0	1	13	1	2	1	8	12	7	5	3	5
NG	5	1	12	0	7	0	1	2	7	3	6	4	8	0
PROPANE	11	3	10	1	11	0	9	0	3	2	3	1	1	0
PJM	4	11	0	20	1	3	1	0	1	3	1	4	5	8
SEI	2	7	2	9	3	1	2	0	0	3	0	1	1	4

Turning next to the coefficients of mean reversion, these are estimated using a modified version of equation 3.3, following the methodology used by Dixit and Pindyck (1994):

$$\Delta x_t = a_0 + a_1 x_{t-1} + \varepsilon_t \ ; \quad \varepsilon_t \sim N(0, \sigma_{regres.}) \tag{3.6}$$

where $x_t = \ln S_t$. Because our primary goal is to estimate the diffusive risk of the model, the regression is applied to the filtered (i.e. without jumps) series when considering the MRJD models; the filtered series is the price returns series that excludes all returns that have previously been identified as jumps. In the case of the simple MR models, the regression of equation 3.6 is applied to the un-filtered (i.e. with jumps) series. Then, for both cases, the estimates for a and σ are calculated using the following equations:

$$a = -\ln(1 + \hat{a}_1) \tag{3.7}$$

$$\sigma = \sigma_{regres.} \sqrt{\frac{2\ln(1+\hat{a}_1)}{(1+\hat{a}_1)^2 - 1}} \tag{3.8}$$

The long-term mean (μ) is calculated from the un-filtered historical time series of each commodity for all models. To estimate the mean reversion rate used after a jump occurs, the following regression is estimated on the un-filtered series:

$$\Delta x_t = a_0 + a_1 x_{t-1} + a_2 x_{t-1} DUM_t + a_3 TIME_t + \varepsilon_t \ ; \quad \varepsilon_t \sim N(0, \sigma_{regres.}) \tag{3.9}$$

where DUM_t is a dummy variable that takes the value of one when a jump occurs and zero otherwise, irrespective of the jumps' direction. A linear time trend is included in the regressions to allow for gradual shifts in the "normal" price (Pindyck, 1999)[18]. The trend coefficient is significant, albeit small in size, in all cases except for the two crack spreads. The presence of a trend in those series is also confirmed visually by looking at the graphs in figure 3-1. Therefore, the de-trended series is used to estimate the different speeds of mean reversion and capture the real expected evolution of the log-price series. The mean reversion

[18] The quadratic trend model is also used in the regressions, which is another extrapolation model commonly used for commodities, however the regression coefficients of the additional term t^2 were insignificant for all the energy markets considered in the study.

rate after a jump occurs is then calculated from the coefficients of equation (3.9) using the following formula:

$$a_{JD} = -\ln(1 + a_1 + a_2) \tag{3.10}$$

All estimates are annualized assuming 252 trading days per year. Finally, one important parameter of the mean reverting process is the half-life, defined as the time required for the log-price to go back half way to its long-run mean from its current level, subject to no other shocks occurring, and is estimated using the following equation:

$$t_{\frac{1}{2}} = \frac{\ln(2)}{a_i} \tag{3.11}$$

$$a_i = \begin{cases} a_1 = a_{JD}, & \text{for returns identified as jumps} \\ a_2 = a, & \text{for smooth returns} \end{cases} \qquad i = 1,2$$

Panel B of table 3-3 presents the two mean reversion rates and the daily standard deviations used in the MR and MRJD models, for all energy markets and the SEI. A general observation is that the estimated mean reversion rate for the returns following a jump is higher for all markets, compared to the diffusive mean reversion rate, which indicates that when a jump occurs prices tend to revert back to their long-term mean faster. The high speed of mean reversion for the spikes is one of the significant features of this model, which also improves the fit of the model to the observed prices in the market. In addition, the estimated mean reversion rate for the un-filtered series is higher when compared to the estimates for the filtered series, suggesting that when spikes are extracted from the sample the coefficient of mean reversion decreases. The exception to that are the three fuel markets (WTI, Heating Oil and Gasoline), Propane and the SEI, where the daily mean reversion rate estimated for both the un-filtered and filtered series is similarly small for all three, in the range of 0.1% to 0.3%. This observation reflects the fact that for the seven year period examined, the fuel markets exhibit a distinctive upward trend, with a small tendency to revert to a long-term mean. However, when looking at the α_{JD} values these are in the range of 0.7% for the SEI, and 0.8% for Propane (the smallest rate amongst the eight energy markets), to 2.1% for Gasoline, indicating that after a jump occurs prices do tend to revert faster to their long-term mean.

It is also noted that the highest speed of mean reversion for both the un-filtered and filtered series occurs for the PJM market, which is also the most volatile market with estimated daily volatility of 15.8% and 13.2%, respectively. When the speed of mean reversion is compared for the spikes amongst the eight energy markets and the SEI, it is observed that PJM has the highest (11.5%), followed by the Heating Oil - WTI crack spread (4.1%). This means that following a positive (negative) jump, prices will be reduced (increased) by 11.5% and 4.1%, respectively each day in order to return to their long-term mean. However, when the impact of the spikes has died-out, prices will revert to their mean at a much lower daily rate of 5.5% and 1.3%, respectively. This is consistent with the stylised fact of energy markets that, following a jump, prices quickly revert back to their long-run mean at a faster rate than when a normal shock occurs.

The results for the calculated half-lives, in days, of the smooth and jumpy returns are also presented in panel B. The half-lives of the jumpy returns are calculated using equation (3.11) and represent the respective durations used in our MRJD models for the higher mean reversion rate (α_{JD}) after a jump occurs. It can be seen that for all energy markets the half-lives of the jumpy returns are much shorter than the ones for the smooth returns; also, the smallest half-life duration for the jumpy returns is observed for the PJM market (6 days), followed by the crack spread of Heating Oil - WTI (17 days), reflecting the higher mean reversion rates observed in those markets. This is expected as the PJM is the most volatile market which experiences frequent and sudden positive and negative jumps, bringing smooth returns back to their long-term level faster, when compared to the other energy markets. The highest half-life duration of jumps is that of the SEI (103 days), followed by Propane (87 days) and NG (72 days). For the fuel markets, the half-life of the jumpy returns for WTI, HO, GASOLINE and the Gasoline – WTI crack spread is 36, 67, 34 and 26 days, respectively. Finally, it is also noted that, as expected, when jumps are removed from the series the estimated volatility is reduced for all energy markets which means that spikes play a very significant role in terms of explaining the volatility in the market.

Turning next to the volatility estimates, the coefficient estimates for the GARCH(1,1) and EGARCH(1,1) models, using equation (3.6) for the specification of mean, are presented in table 3-7. The regression is applied to both the un-filtered and filtered series, with the estimates used for the MR and MRJD models, respectively. Because results are qualitatively similar, only those estimated from the un-filtered historical series are reported in the table.

All GARCH coefficients are significant at the 5% level, verifying the presence of time-varying volatility in all energy markets and the SEI. In addition, it is observed that the sum of the coefficients β_1 and β_2 for the GARCH models is greater than the coefficient β_3 of the EGARCH model, indicating that the volatility persistence in the latter case is reduced, which is consistent with the literature on volatility models. Looking at the estimates for the β_2 coefficients of the EGARCH models, which measure the leverage effect, it is observed that they are significant in all cases indicating the presence of asymmetries in the way past shocks affect the current volatility. For the WTI, Heating Oil and Heating Oil – WTI crack spread returns, the coefficient estimate β_2 is negative at the five percent level, indicating the presence of a "leverage" effect; in other words negative shocks have greater impact on volatility than positive shocks. One possible explanation for this finding may be that price shocks for the aforementioned markets are more supply- than demand-driven, due to the fact that the market has been operating at the steep part of the supply stack in recent years. This phenomenon can be attributed to the very low spare capacity in world energy production, with small supply disruptions causing large price increases due to difficulties of rapid replacement of any production shortfalls. This is in contrast to what one expects to find in commodity markets as well as recent empirical evidence by, among others Baumeister and Peersman (2008), who point out that oil price surges can almost entirely be explained by shifts in global demand (positive shocks), with the contribution of supply shocks (negative shocks) on crude oil price volatility diminishing considerably over the recent years. This inconsistency in the findings can be attributed to the fact that over the past few years other exogenous factors, in addition to the market fundamentals of supply and demand, have been driving the oil markets. As a result, the fuel markets in particular have become more prone to movements of a much broader range of financial indicators like international currencies' exchange rate movements relative to the US dollar, interest rates, equity markets' performance, as well as the widespread use of "paper" derivative products both for the purposes of risk management as well as for speculation.

Table 3-7: GARCH and EGARCH coefficient estimates from the un-filtered series.

The regression results of equation (3.6) are presented, considering a GARCH and an EGARCH estimate for the variance, respectively. The regression is applied to both the un-filtered and filtered series, with the estimates used for the MR and MRJD models, respectively. Results are qualitatively similar and only those estimated from the un-filtered historical series are reported in the table. P-values are in brackets. The GARCH and EGARCH volatility equations are the following:

$$\sigma_t = \sqrt{\beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 * \sigma_{t-1}^2} \quad [GARCH(1,1)]$$

$$\sigma_t = \sqrt{e^{\beta_0 + \beta_1 * \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 * \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 * \ln(\sigma_{t-1}^2)}} \quad [EGARCH(1,1)]$$

	WTI	HO	GASOLINE	CS_GASOLINE_WTI	CS_HO_WTI	NG	PROPANE	PJM	SEI
GARCH(1,1)									
β0	0.00003	0.00006	0.00012	0.00000	0.00000	0.00006	0.00004	0.00066	0.00006
	(0.00008)	(0.00000)	(0.00000)	(0.00002)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
β1	0.05992	0.09713	0.09090	0.13803	0.15535	0.13596	0.14783	0.13640	0.09791
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
β2	0.88950	0.81687	0.78194	0.88450	0.84440	0.86011	0.77278	0.84627	0.84029
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
EGARCH(1,1)									
β0	-0.69575	-0.71312	-0.86639	-0.31057	-1.34905	-0.32579	-1.58968	-0.30804	-0.49275
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
β1	0.10618	0.19570	0.19953	0.20868	0.35897	0.21273	0.36064	0.24126	0.17839
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
β2	-0.10648	-0.00630	0.00658	0.06972	-0.03414	0.07314	0.02848	0.03709	0.04338
	(0.01404)	(0.01002)	(0.01179)	(0.00822)	(0.01211)	(0.00896)	(0.00887)	(0.01212)	(0.01366)
β3	0.91928	0.92322	0.89790	0.98322	0.88680	0.97227	0.82680	0.96604	0.94866
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)

However, for the remaining energy markets, the asymmetry parameter is positive at the 5% significance level, which implies that positive shocks, as described by unexpected demand shocks, have greater impact on volatility compared to negative shocks, which is consistent with the presence of an "inverse leverage" effect. It can be argued that since the beginning of the new millennium, worldwide economic growth gave rise to stronger than expected demand for energy products that are critical to the global economy. As a result, demand outpaced the near-term ability of the market to bring forth proportionate additional supplies; the resulting tightness in the global energy markets caused prices to increase, and the impact of this increase has been felt throughout the whole chain of production. Along the same lines, Kanamura (2009) finds that demand for US natural gas prices is highly inelastic in the short-term, with the energy use being independent of the price change, suggesting the presence of an "inverse leverage" effect. So, when an unexpected demand shock occurs, energy prices are expected to exhibit this "inverse leverage" effect, a conclusion that can be drawn from our results; this is also consistent with the findings in Eydeland and Wolyniec (2003) regarding the energy markets.

3.5. Simulation of Estimated Models

After estimating the parameters of the model, Monte Carlo (MC) is used to simulate the behaviour of each market; the simulations are carried out based on equation (3.4) and the paths are simulated 100,000 times. The starting date of the simulations is the same as the initial date of the historical prices, i.e. 12/09/2000, with the horizon of the simulated distribution extending up to 12/09/2007; in total 1827 trading days. Since the main purpose of this chapter is to propose models that can capture the distributional characteristics of the underlying market, MC simulation is a valuable tool for helping with the selection criteria of the best model. Clewlow et al. (2000a; 2000b) use Monte Carlo simulations on different variations of the MRJD model and demonstrate how these models can be used to price energy options whose payouts are path-dependent, or rely on multiple energies. In addition, other applications of MC simulation include pricing of various energy derivatives contracts, policy development and risk monitoring. Hence, because the goal is to determine whether the proposed models can capture the major characteristics of the distribution of energy spot prices, in what follows, a distribution analysis is performed which will help analyze the price behaviour over a period of time and, at the same time, assist with testing, benchmarking, and selecting the most appropriate model for describing each one of the energy markets examined.

The descriptive statistics of the actual log-returns' series, along with the average per time-step simulated paths for all models used in the analysis, are presented in table 3-8. The average of the simulated values at time t across all possible paths is calculated as:

$$S_t^s = \sum_{\omega=1}^{n} \frac{S_{t,\omega}^s}{n} \tag{3.11}$$

where, $S_{t,\omega}$ is the simulated spot price of path ω at time t, and n is the number of MC simulations. From table 3-8 it can be seen that for almost all the energy markets examined, the models that most closely match the skewness and kurtosis of the underlying distributions are the ones that incorporate jumps, namely the MRJD-OLS, the MRJD-GARCH and the MRJD-EGARCH. It can also be noted that in the case of WTI, the skewness produced with the MRJD-OLS model is identical to the actual one, whereas the kurtosis value is the highest among the competing models, thus also following very closely the actual one. It is only for

HO and Propane that the MR-GARCH(1,1) model is able to better match the skewness and kurtosis of the actual price path. Therefore, it seems that the proposed approach to allow for a different speed of mean reversion after a jump occurs, improves the fit that the models have in terms of capturing the skewness and kurtosis of the actual series, for almost all energy markets and the SEI.

Table 3-8: Distributional comparison of the actual spot log-price returns to the average per time-step simulated path.

Distributional comparison of the actual spot logarithmic-price returns to the average per time-step simulated path for each model specification. Where $S_t^s = \sum_{\omega=1}^{n} \frac{S_{t,\omega}^s}{n}$ is the average of the simulated values at time t across all possible paths, $S_{t,\omega}$ is the simulated spot price of path ω at time t, and n is the number of MC simulations. The test-statistic numbers are reported for the Kolmogorov-Smirnov (K-S) test, with an asterisk (*) indicating that the null is accepted that the two samples are from the same continuous distribution, at the 5% significance level. The models with the smallest K-S test-statistic value are indicated with a (+).

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	K-S
WTI								
Actual Path	0.00	0.00	0.11	-0.17	0.02	-0.45	6.48	
GBM	0.00	0.00	0.08	-0.08	0.02	0.00	3.00	0.501
MR-OLS	0.00	0.00	0.12	-0.17	0.03	-0.16	3.87	0.058
MR-GARCH(1,1)	0.00	0.00	0.12	-0.17	0.03	-0.17	3.94	0.059
MR-EGARCH (1,1)	0.00	0.00	0.13	-0.17	0.03	-0.16	3.94	0.055
MRJD-OLS	0.00	0.00	0.13	-0.21	0.03	-0.45	5.39	0.056
MRJD-GARCH(1,1)	0.00	0.00	0.14	-0.21	0.04	-0.34	4.91	0.055
MRJD-EGARCH (1,1)	0.00	0.00	0.13	-0.21	0.03	-0.42	5.28	0.054+
HO								
Actual Path	0.00	0.00	0.12	-0.19	0.03	-0.27	6.69	
GBM	0.00	0.00	0.09	-0.09	0.03	0.00	3.00	0.491
MR-OLS	0.00	0.00	0.14	-0.19	0.04	-0.10	3.92	0.067
MR-GARCH(1,1)	0.00	0.00	0.14	-0.19	0.04	-0.10	4.03	0.065
MR-EGARCH (1,1)	0.00	0.00	0.14	-0.20	0.04	-0.09	3.92	0.065
MRJD-OLS	0.00	0.00	0.20	-0.19	0.04	0.08	4.97	0.060
MRJD-GARCH(1,1)	0.00	0.00	0.21	-0.19	0.04	0.07	4.76	0.057
MRJD-EGARCH (1,1)	0.00	0.00	0.20	-0.19	0.04	0.08	4.83	0.056+
GASOLINE								
Actual Path	0.00	0.00	0.18	-0.18	0.03	-0.26	6.76	
GBM	0.00	0.00	0.10	-0.10	0.03	0.00	3.00	0.484
MR-OLS	0.00	0.00	0.20	-0.20	0.04	-0.09	3.94	0.044*
MR-GARCH(1,1)	0.00	0.00	0.20	-0.19	0.04	-0.09	4.00	0.045
MR-EGARCH (1,1)	0.00	0.00	0.20	-0.20	0.04	-0.09	3.91	0.046
MRJD-OLS	0.00	0.00	0.24	-0.26	0.04	-0.11	6.04	0.044*+
MRJD-GARCH(1,1)	0.00	0.00	0.24	-0.26	0.04	-0.10	5.79	0.045
MRJD-EGARCH (1,1)	0.00	0.00	0.24	-0.26	0.04	-0.10	5.85	0.045
CS_GASOLINE_WTI								
Actual Path	0.00	0.00	0.12	-0.16	0.01	-0.92	29.30	
GBM	0.00	0.00	0.05	-0.05	0.01	0.00	3.00	0.463
MR-OLS	0.00	0.00	0.12	-0.16	0.02	-0.32	9.47	0.029*
MR-GARCH(1,1)	-0.01	0.00	2.34	-2.57	0.48	-0.27	8.62	0.297
MR-EGARCH (1,1)	0.00	0.00	0.12	-0.16	0.02	-0.29	8.52	0.025*
MRJD-OLS	0.00	0.00	0.11	-0.08	0.02	1.15	6.69	0.023*+
MRJD-GARCH(1,1)	0.00	0.00	0.42	-0.43	0.08	-0.03	6.70	0.028*
MRJD-EGARCH (1,1)	0.00	0.00	0.13	-0.11	0.03	0.44	4.58	0.024*
CS_HO_WTI								
Actual Path	0.00	0.00	0.06	-0.05	0.01	0.37	10.67	
GBM	0.00	0.00	0.03	-0.03	0.01	0.00	3.00	0.474
MR-OLS	0.00	0.00	0.06	-0.06	0.01	0.13	4.89	0.031*
MR-GARCH(1,1)	0.00	0.00	0.11	-0.12	0.02	0.02	8.23	0.031*
MR-EGARCH (1,1)	0.00	0.00	0.06	-0.06	0.01	0.10	4.66	0.032*
MRJD-OLS	0.00	0.00	0.08	-0.06	0.01	0.45	8.28	0.029*
MRJD-GARCH(1,1)	0.00	0.00	0.13	-0.13	0.02	0.03	7.06	0.023*
MRJD-EGARCH (1,1)	0.00	0.00	0.08	-0.07	0.01	0.20	6.33	0.022*+

Table cont.								
NG								
Actual Path	0.00	0.00	0.62	-0.57	0.05	0.73	32.85	
GBM	0.00	0.00	0.17	-0.17	0.05	0.00	3.00	0.453
MR-OLS	0.00	0.00	0.62	-0.57	0.07	0.26	10.42	0.059
MR-GARCH(1,1)	0.00	0.00	0.73	-0.73	0.11	-0.06	8.83	0.070
MR-EGARCH (1,1)	0.00	0.00	0.63	-0.57	0.08	0.13	7.44	0.056
MRJD-OLS	0.00	0.00	0.49	-0.37	0.07	0.90	9.59	0.049
MRJD-GARCH(1,1)	0.00	0.00	0.58	-0.55	0.11	0.12	5.66	0.052
MRJD-EGARCH (1,1)	0.00	0.00	0.51	-0.40	0.08	0.43	6.16	0.049$^+$
PROPANE								
Actual Path	0.00	0.00	0.36	-0.24	0.02	1.61	45.15	
GBM	0.00	0.00	0.08	-0.08	0.02	0.00	3.00	0.505
MR-OLS	0.00	0.00	0.36	-0.24	0.03	0.57	13.52	0.110
MR-GARCH(1,1)	0.00	0.00	0.36	-0.24	0.03	0.60	14.71	0.107
MR-EGARCH (1,1)	0.00	0.00	0.36	-0.25	0.03	0.55	13.18	0.108
MRJD-OLS	0.00	0.00	0.23	-0.19	0.03	0.55	10.39	0.096
MRJD-GARCH(1,1)	0.00	0.00	0.24	-0.21	0.04	0.20	6.34	0.093
MRJD-EGARCH (1,1)	0.00	0.00	0.23	-0.20	0.04	0.33	7.19	0.092$^+$
PJM								
Actual Path	0.00	0.00	0.96	-1.43	0.15	0.06	12.78	
GBM	0.00	0.00	0.52	-0.52	0.15	0.00	2.99	0.467
MR-OLS	0.00	0.00	1.09	-1.43	0.22	0.02	5.34	0.044*
MR-GARCH(1,1)	0.00	0.00	1.16	-1.46	0.23	-0.01	5.97	0.041*
MR-EGARCH (1,1)	0.00	0.00	1.14	-1.43	0.24	-0.02	4.99	0.039*$^+$
MRJD-OLS	0.00	0.00	1.42	-1.46	0.23	-0.06	8.03	0.046
MRJD-GARCH(1,1)	0.00	0.00	1.63	-1.69	0.31	-0.09	6.00	0.041*
MRJD-EGARCH (1,1)	0.00	0.00	1.46	-1.51	0.26	-0.11	6.57	0.043*
SEI								
Actual Path	0.00	0.00	0.17	-0.24	0.03	0.24	8.21	
GBM	0.00	0.00	0.11	-0.11	0.03	0.00	3.00	0.480
MR-OLS	0.00	0.00	0.20	-0.24	0.04	0.09	4.29	0.026*
MR-GARCH(1,1)	0.00	0.00	0.21	-0.24	0.04	0.08	4.39	0.024*
MR-EGARCH (1,1)	0.00	0.00	0.21	-0.24	0.05	0.07	4.19	0.023*
MRJD-OLS	0.00	0.00	0.31	-0.24	0.05	0.50	7.02	0.021*
MRJD-GARCH(1,1)	0.00	0.00	0.32	-0.26	0.05	0.32	6.11	0.022*
MRJD-EGARCH (1,1)	0.00	0.00	0.31	-0.24	0.05	0.40	6.26	0.017*$^+$

To formally compare the actual returns' distribution with the average of the simulated series per time-step, the two-sample Kolmogorov-Smirnov (K-S) test is calculated. The two-sample K-S test is a non-parametric test for the equality of two probability distributions. The test effectively compares the distance between the actual and the simulated distribution around their mean, and the reported statistic is the maximum vertical deviation between the two curves. One of the advantages of the K-S test is that the value of the statistic is not affected by scale changes like using the logarithm of prices, as is the case in the data; it is a robust test that only considers the relative distributions of the data. In this case, the first sample $X_1,...,X_m$ of size $m=1826$ observations, which are the actual spot log-price returns, has a distribution with cumulative density function (c.d.f.) $F(x)$, and the second will be in every case the average per time-step simulated sample $Y_1,...,Y_m$ of the same size $m=1826$, having a distribution with c.d.f. $G(x)$. The null hypothesis of the K-S test is that F and G are from the same continuous distribution, with the alternative hypothesis that they are from different continuous distributions: $H_0 : F = G$ vs. $H_1 : F \neq G$

Results from the K-S tests are also presented in table 3-8; based on the calculated K-S test statistic the null hypothesis that the actual and the average per time-step simulated distributions are identical is accepted at the 5% significance level, for the Gasoline market, the two crack spreads of crude oil with heating oil and gasoline, the PJM market, and the SEI. This is true for most models with the exception of the GBM where the null hypothesis of equality of distributions is overwhelmingly rejected. Comparing the values between the different models it can be seen that generally the models that incorporate jumps have the lowest value for the K-S test indicating that, at least nominally, these provide the closest match to the underlying distribution. For the remaining markets, although the null hypothesis that the samples are drawn from an identical distribution is rejected, the value of the K-S statistic is lower for the models that contain jumps in their terms. Furthermore, in table 3-8, the models with the smallest K-S test-statistic value are indicated with a (+). It can be seen that the models producing the smallest K-S test-statistic values are the MRJD-EGARCH(1,1) for WTI, HO, CS_HO_WTI, NG, Propane, and the SEI, the MRJD-OLS model for Gasoline and CS_Gasoline_WTI markets, and finally the MR-EGARCH(1,1) for the PJM market. Overall, from the distributional comparison of the actual log-price returns and the average per time-step simulated returns, it can be concluded that the addition of jumps in the simple mean reversion model - while allowing for a different speed of mean reversion after a jump occurs for a period of time equal to the estimated half-life of the jumpy returns - as well as the addition of the EGARCH (1,1) process, improves the fit of the simulated returns to the actual distributions, for most of the energy markets under investigation and the SEI.

Furthermore, the relative goodness of fit for the various models is assessed by examining how closely each endogenous variable from the simulations tracks the actual spot logarithmic prices for the seven year period examined. Clewlow and Strickland (2000) use the likelihood ratio test and the Schwartz Bayesian Information criterion to compare their various models. In this case, because the simulations' goodness of fit needs to be tested, three quantitative and one qualitative measure is used to check how closely the individual variables track their corresponding data series. The three quantitative measures are the root-mean-square error (RMSE), the root-mean-square percent error (RMSE %), and Theil's inequality coefficient known as Theil's U (Theil, 1961). The RMS error measures the deviation of the average simulated log-price from its actual time path, while the RMS percent error evaluates the magnitude of the RMS error as a percentage of the underlying spot price; finally, Theil's U measures the RMS error in relative terms.

Table 3-9 presents the comparison results for the proposed models based on the RMSE, RMSE%, and Theil's U metrics. It can be seen that, based on all three comparative statistical measures, the MRJD-EGARCH (1,1) is the best model for tracking the actual time path of the WTI and Gasoline log-prices with the statistics for the MRJD-OLS being very similar. For the Heating Oil market, the best model appears to be the MRJD-OLS, which is marginally better than the MRJD-EGARCH (1,1) on the basis of the RMSE and RMSE% statistics. For all the remaining markets and the SEI, the model that best captures the price paths of the underlying series appears to be the MRJD-OLS, a result which is verified by all three statistical measures, with the MRJD-EGARCH exhibiting the second-best performance. It is only for the Gasoline – WTI crack spread that the MR-OLS and MR-EGARCH (1,1) models appear to perform better than the respective models incorporating jumps. Hence, the initial motivation of this chapter to use Poisson jumps and to allow for two different speeds of mean reversion in the modelling procedure, to explain the spikier behaviour of the energy log-prices, combined with an EGARCH specification for the variance, is validated by the above findings.

Table 3-9: Comparison of the models' goodness of fit to the actual spot log-prices.

Simulation error statistics on the difference between actual versus average simulated price paths. RMSE, RMSE %, and Theil's U are respectively calculated as:

$$RMSE=\sqrt{\frac{\sum_{t=1}^{T}\left(S_t^s-S_t^a\right)^2}{T}},\quad RMSE\%=\sqrt{\frac{\sum_{t=1}^{T}\left(\frac{S_t^s-S_t^a}{S_t^a}\right)^2}{T}}\quad \text{and}\quad U=\sqrt{\frac{\sum_{t=1}^{T}\left(S_t^s-S_t^a\right)^2}{T}}\Bigg/\sqrt{\frac{\sum_{t=1}^{T}\left(S_t^s\right)^2}{T}}+\sqrt{\frac{\sum_{t=1}^{T}\left(S_t^a\right)^2}{T}}$$

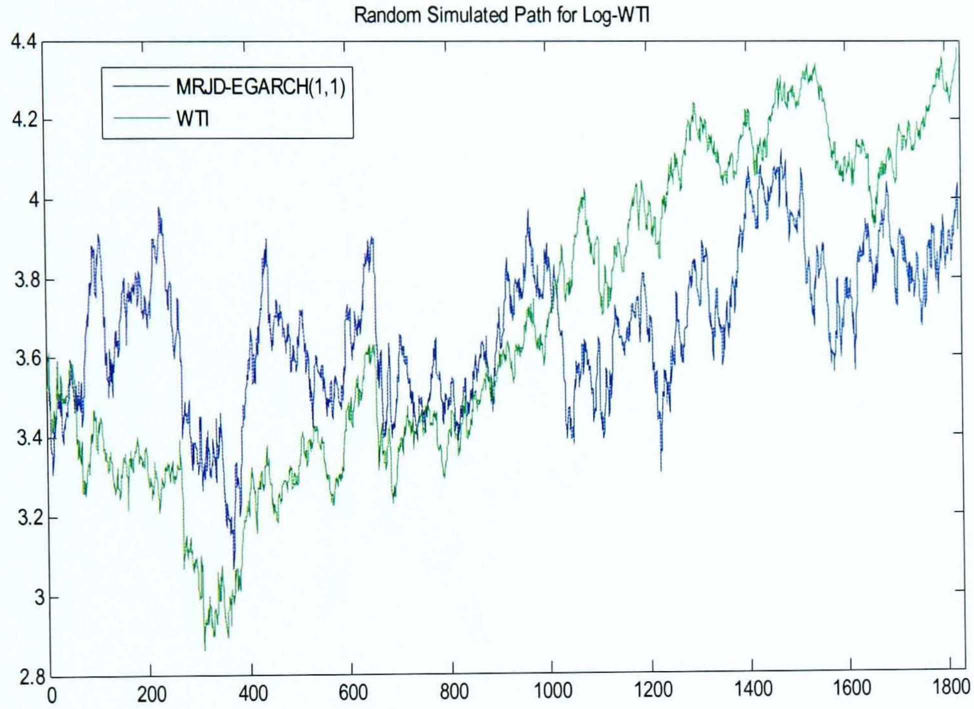
where $S_t^s=\sum\frac{S_{t,\omega}^s}{\omega}$ is the average of the simulated values at time t across all possible paths, $S_{t,\omega}$ is the simulated spot price of path ω at time t, ω is the number of MC simulations, S_t^a is the actual value on any given time-step, and T is the number of discretised periods in the simulation.

	GBM	MR-OLS	MR-GARCH(1,1)	MR-EGARCH (1,1)	MRJD-OLS	MRJD-GARCH(1,1)	MRJD-EGARCH (1,1)
WTI							
RMSE	0.695	0.652	0.651	0.652	0.385	0.399	0.387
RMSE %	0.188	0.169	0.168	0.168	0.099	0.103	0.100
Theil's U	0.090	0.096	0.095	0.096	0.053	0.055	0.053
HO							
RMSE	0.792	0.634	0.635	0.666	0.379	0.390	0.385
RMSE %	0.207	0.158	0.159	0.167	0.096	0.099	0.098
Theil's U	0.098	0.088	0.089	0.093	0.050	0.051	0.051
GASOLINE							
RMSE	0.860	0.528	0.524	0.554	0.377	0.382	0.380
RMSE %	0.218	0.131	0.130	0.138	0.095	0.096	0.096
Theil's U	0.108	0.071	0.070	0.074	0.049	0.050	0.049
CS_GASOLINE WTI							
RMSE	0.361	0.067	7.629	0.075	0.166	0.401	0.177
RMSE %	0.077	0.014	1.620	0.016	0.035	0.085	0.038
Theil's U	0.039	0.007	0.668	0.008	0.017	0.043	0.019
CS_HO_WTI							
RMSE	0.224	0.048	0.092	0.054	0.045	0.105	0.054
RMSE %	0.048	0.010	0.020	0.012	0.010	0.022	0.012
Theil's U	0.024	0.005	0.010	0.006	0.005	0.011	0.006
NG							
RMSE	1.371	0.477	1.263	0.627	0.508	0.814	0.566
RMSE %	0.857	0.301	0.781	0.392	0.376	0.539	0.397
Theil's U	0.377	0.145	0.324	0.195	0.135	0.233	0.155
PROPANE							
RMSE	0.739	0.573	0.558	0.590	0.327	0.386	0.353
RMSE %	0.178	0.131	0.128	0.135	0.080	0.092	0.085
Theil's U	0.084	0.072	0.070	0.074	0.038	0.046	0.042
PJM							
RMSE	4.051	0.497	0.565	0.593	0.546	0.930	0.641
RMSE %	1.019	0.126	0.144	0.151	0.140	0.238	0.164
Theil's U	0.449	0.064	0.074	0.078	0.071	0.124	0.084
SEI							
RMSE	0.884	0.476	0.481	0.514	0.385	0.428	0.404
RMSE %	0.185	0.098	0.099	0.106	0.083	0.091	0.087
Theil's U	0.092	0.052	0.052	0.056	0.040	0.045	0.042

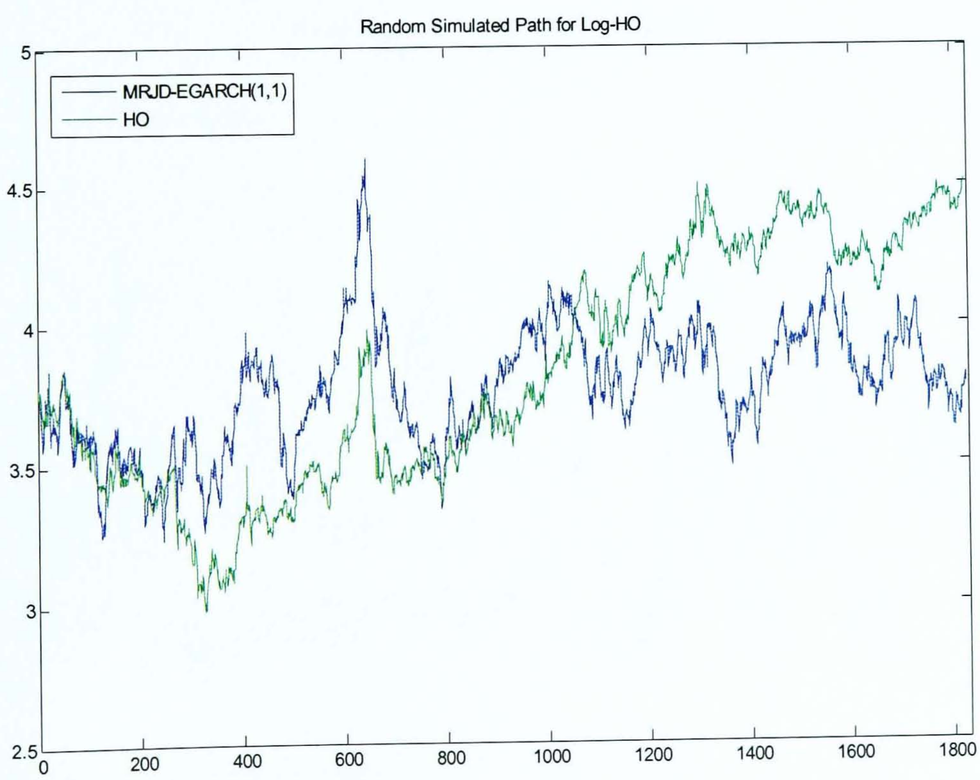
Although the statistics presented above are very helpful by giving an indication on the relative quality of each model, another important criterion is how well the model captures the turning points in the data. For that, a very useful test can be a simple visual inspection of the sample price processes and the associated log-return prices (Clewlow and Strickland, 2000). Therefore, a graphical comparison of the simulated prices with the actual data is produced, plotting at first a random simulated price path and the observed data, and at second the distribution of the daily log-returns as a histogram and the daily log-returns for the average per time-step simulated prices as an overlaid line. Figure 3-5 (Panels A to I) shows the plot of a random simulated path for the MRJD-EGARCH (1,1) model over the actual path of the log-prices, for all energy markets and the SEI. It can be seen that the MRJD-EGARCH (1,1) model can capture most of the major turning points in the data, tracking close enough the actual path. In particular, a major feature of the proposed model is the fact that following a jump in the prices, the price series mean-reverts to its mean at a faster rate which is consistent with the pattern observed in the market. In addition, Figure 3-6 (Panels A to I) shows the distribution of the actual spot daily log-returns as a histogram and the daily log-returns for the average per time-step simulated prices as an overlaid line, for all energy markets and the SEI. It is observed that the MRJD-EGARCH (1,1) model captures very well the kurtosis and the skewness of the actual log-returns for almost all energy markets and the SEI. This observation enhances the findings from tables 3-8 and 3-9, where the MRJD model with an EGARCH specification for the variance is amongst the best performing models in terms of approximating the actual returns' distribution.

Figure 3-5: Random simulated path of spot log-prices from the MRJD-EGARCH (1,1) model plotted against the actual path, for all energy markets.

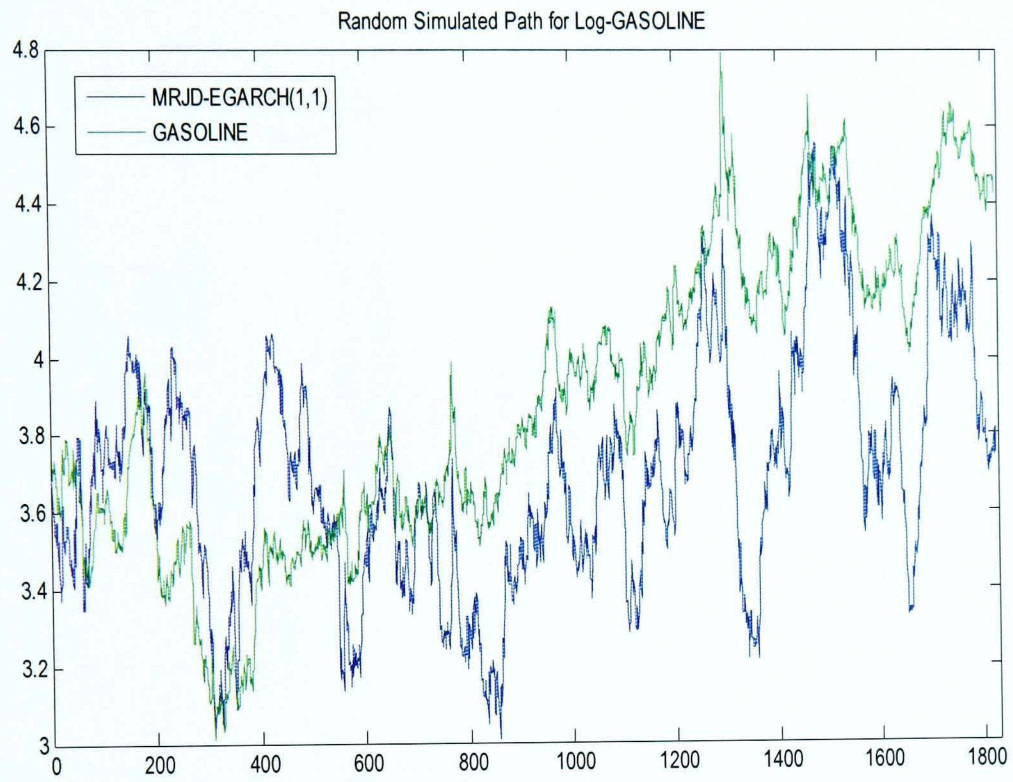
Panel A: Crude Oil – West Texas Intermediate (WTI)



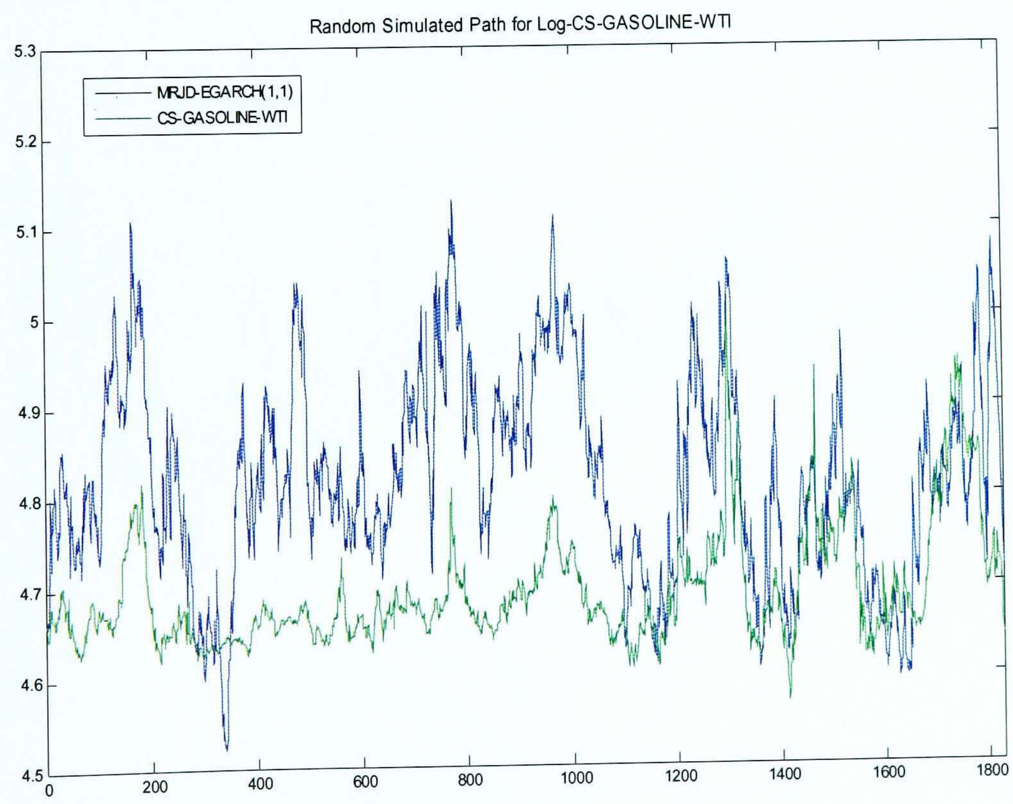
Panel B: Heating Oil - New York Harbour No.2 Fuel Oil (HO)



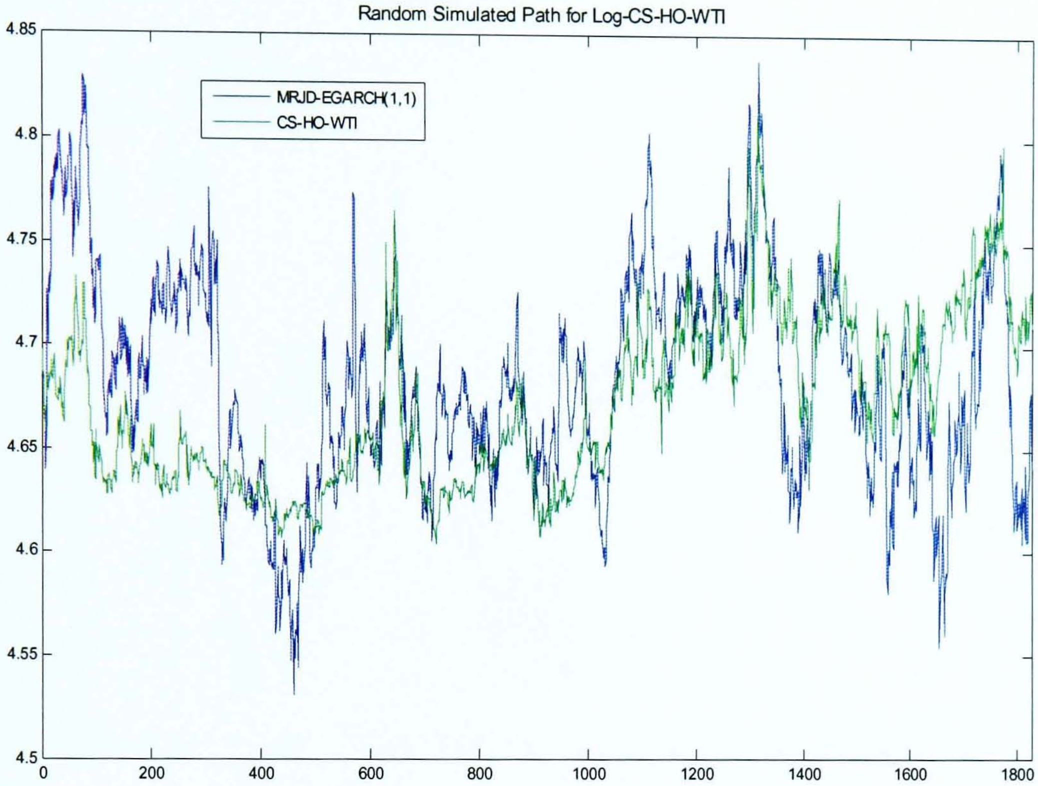
Panel C: Gasoline Oil - New York Harbour RBOB (Gasoline)



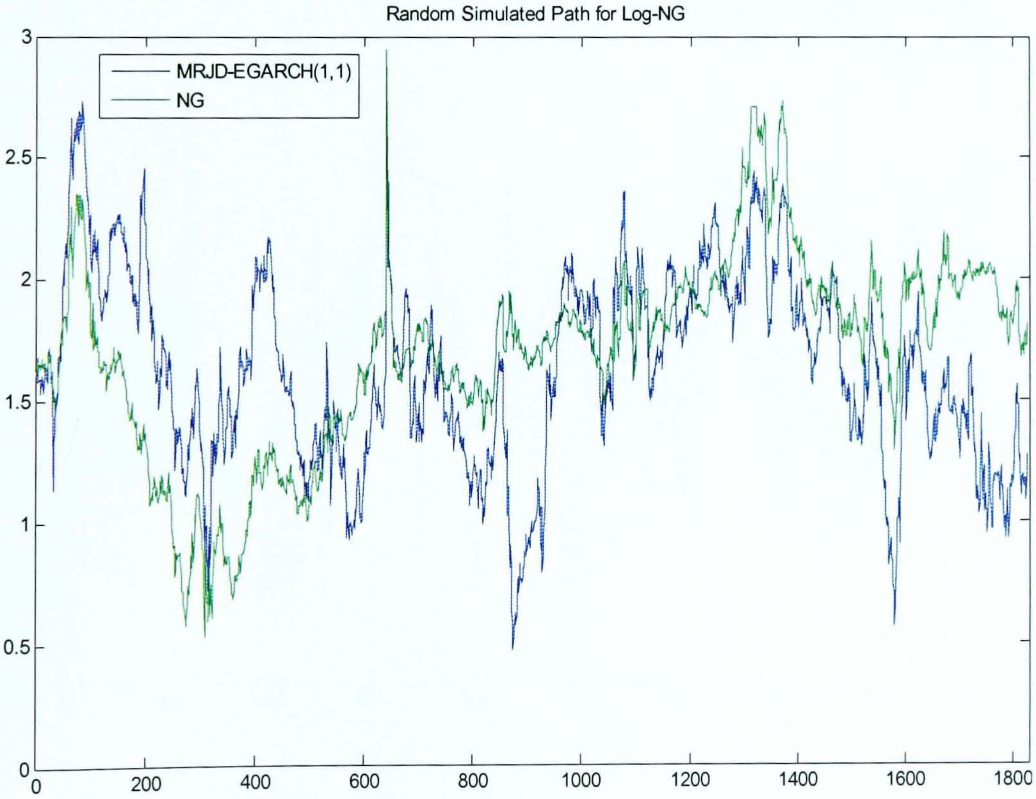
Panel D: 1-1 Crack Spread of Gasoline with WTI (CS-Gasoline-WTI)



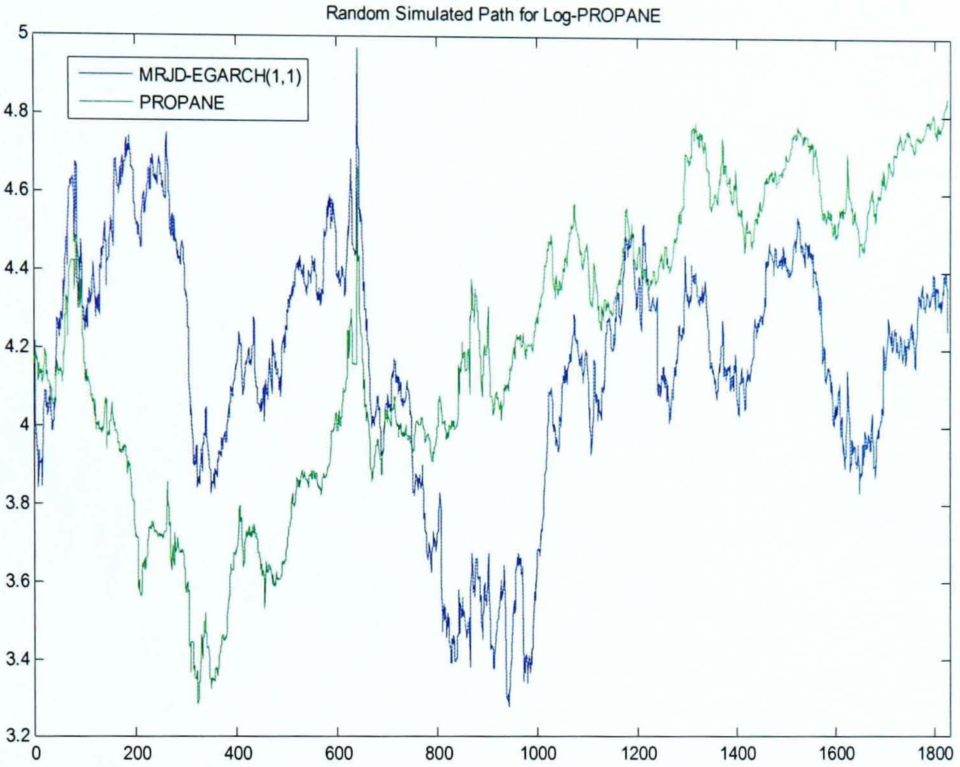
Panel E: 1-1 Crack Spread of Heating Oil with WTI (CS-HO-WTI)



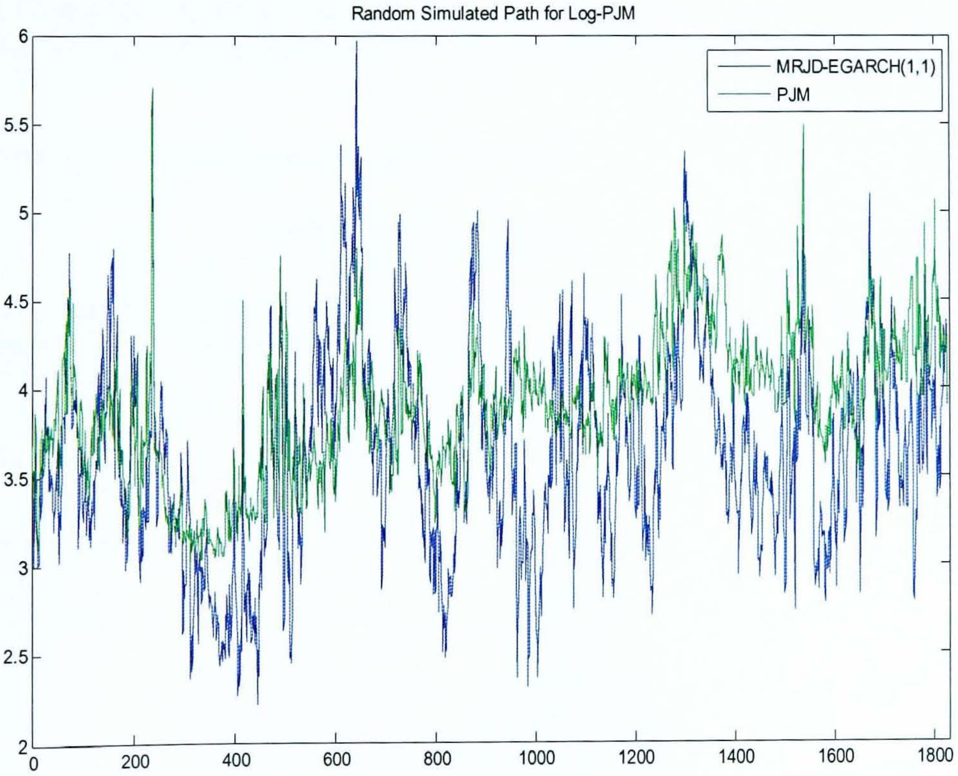
Panel F: Natural Gas - Henry Hub (NG)



Panel G: Propane - Mont Belvieu Texas (Propane)



Panel H: Interconnection Electricity Firm On Peak Price Index (PJM)



Panel I: Spot Energy Index (SEI)

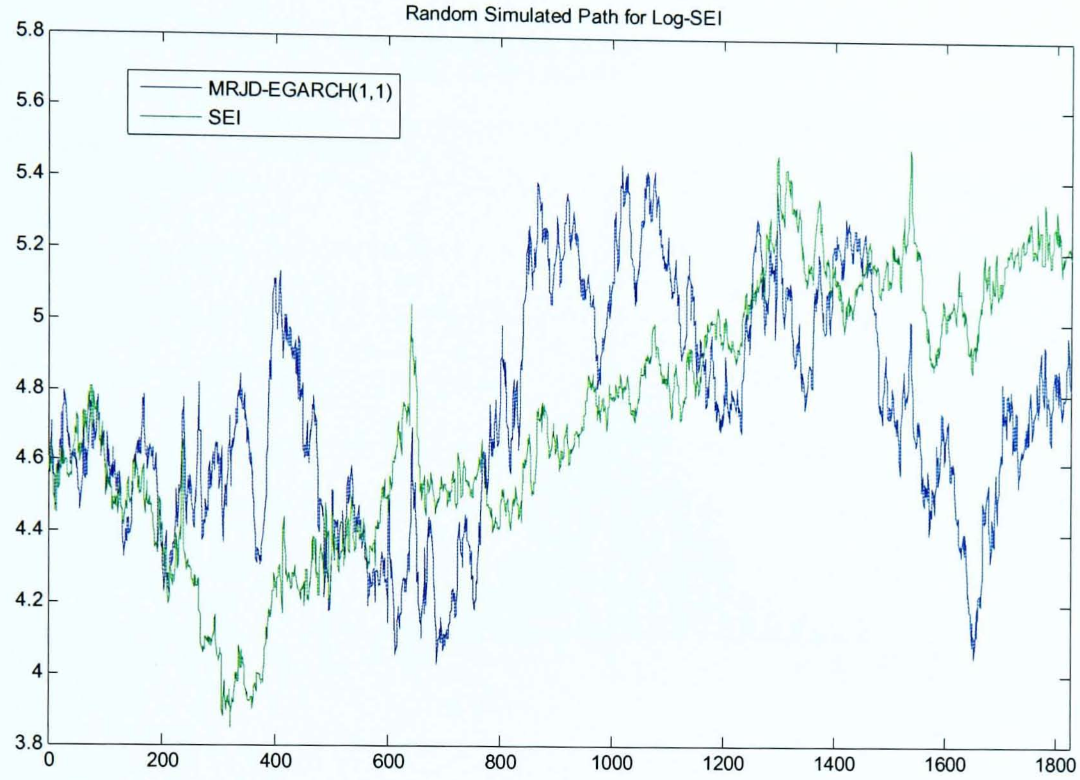
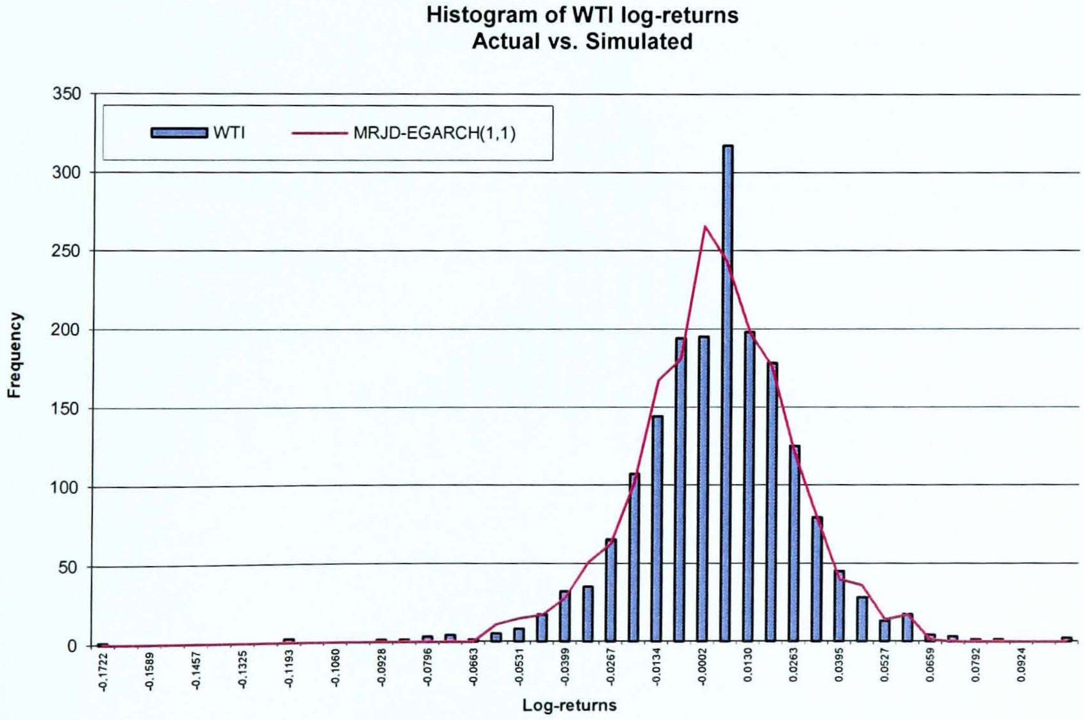
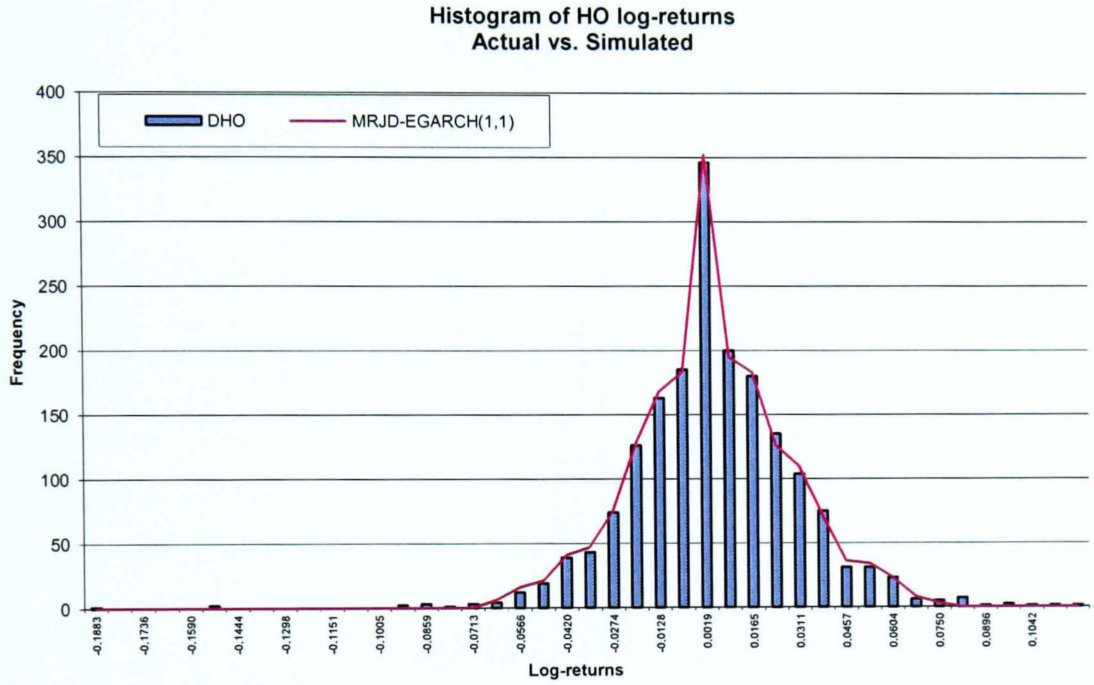


Figure 3-6: Histogram of the average simulated spot log-price returns per time-step for the MRJD-EGARCH (1,1) model plotted as a solid line against the actual returns, for all energy markets.

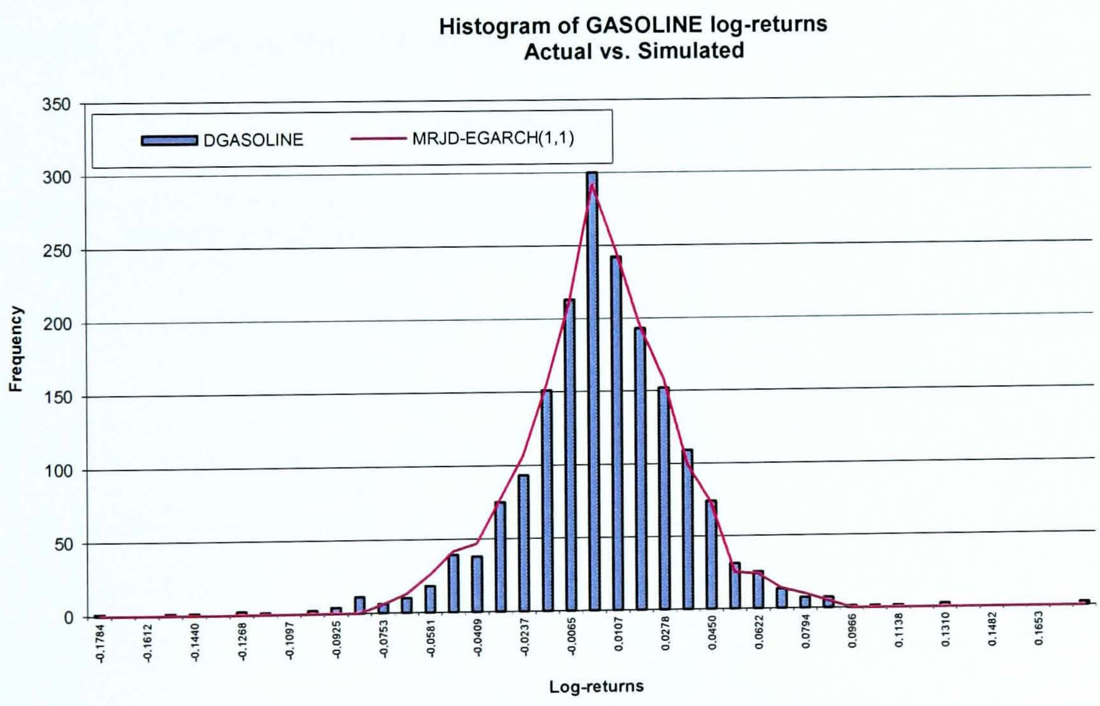
Panel A: Crude Oil – West Texas Intermediate (WTI)



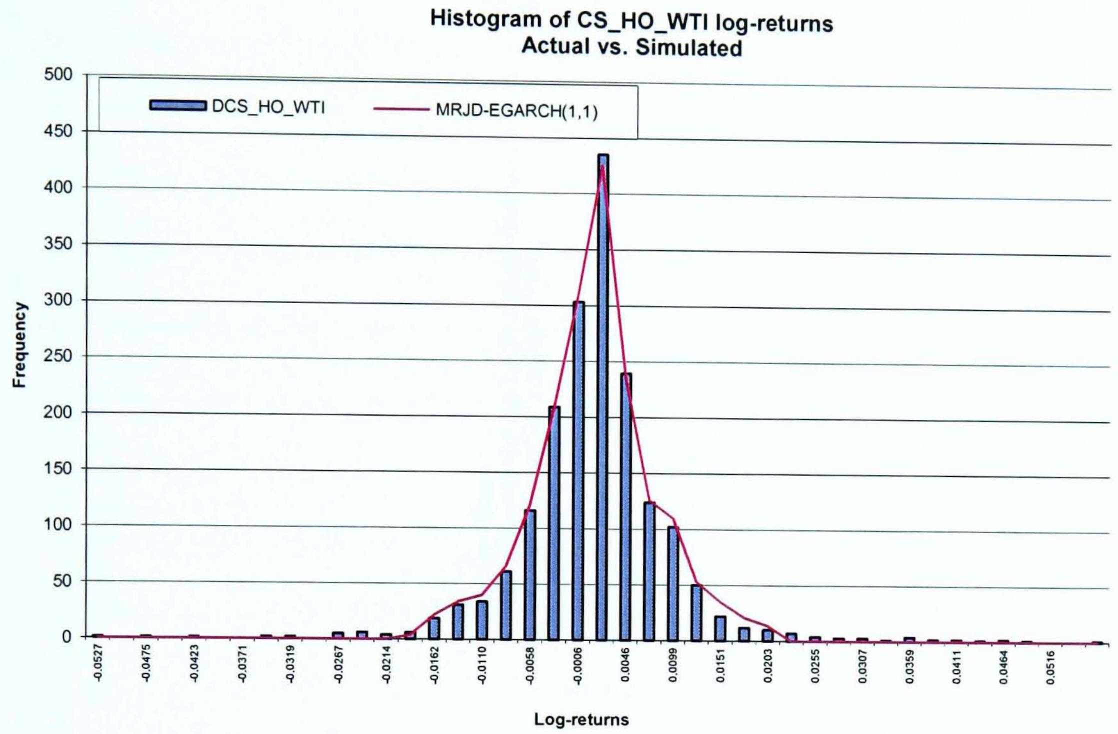
Panel B: Heating Oil - New York Harbour No.2 Fuel Oil (HO)



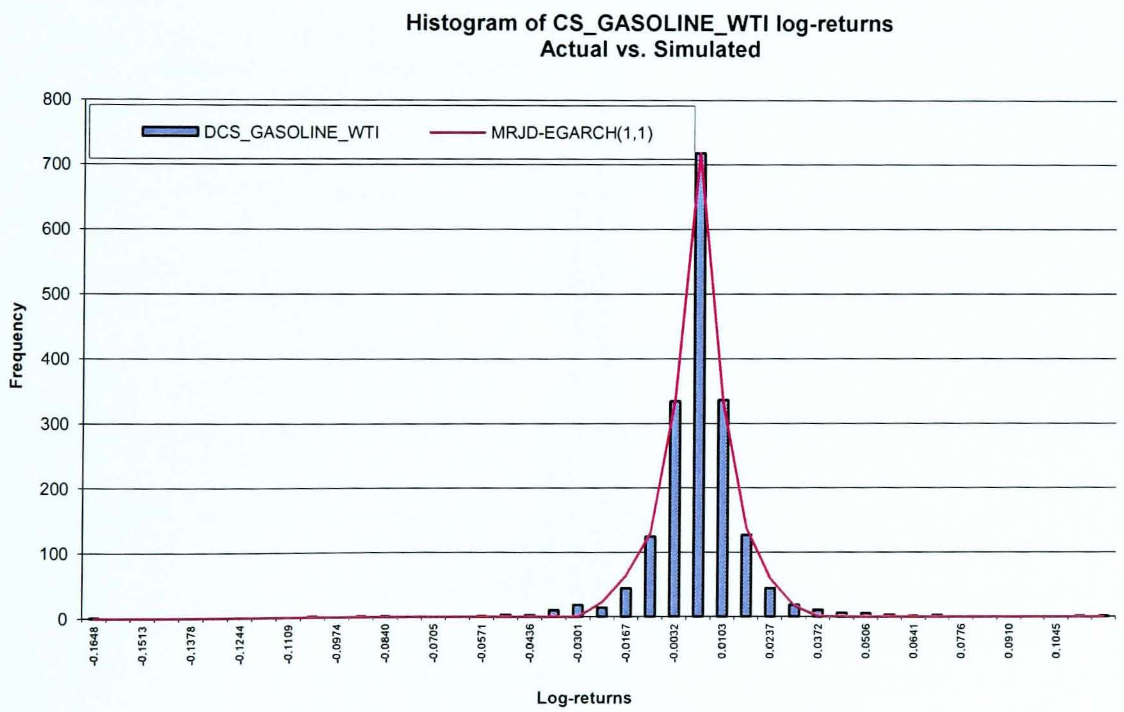
Panel C: Gasoline Oil - New York Harbour RBOB (Gasoline)



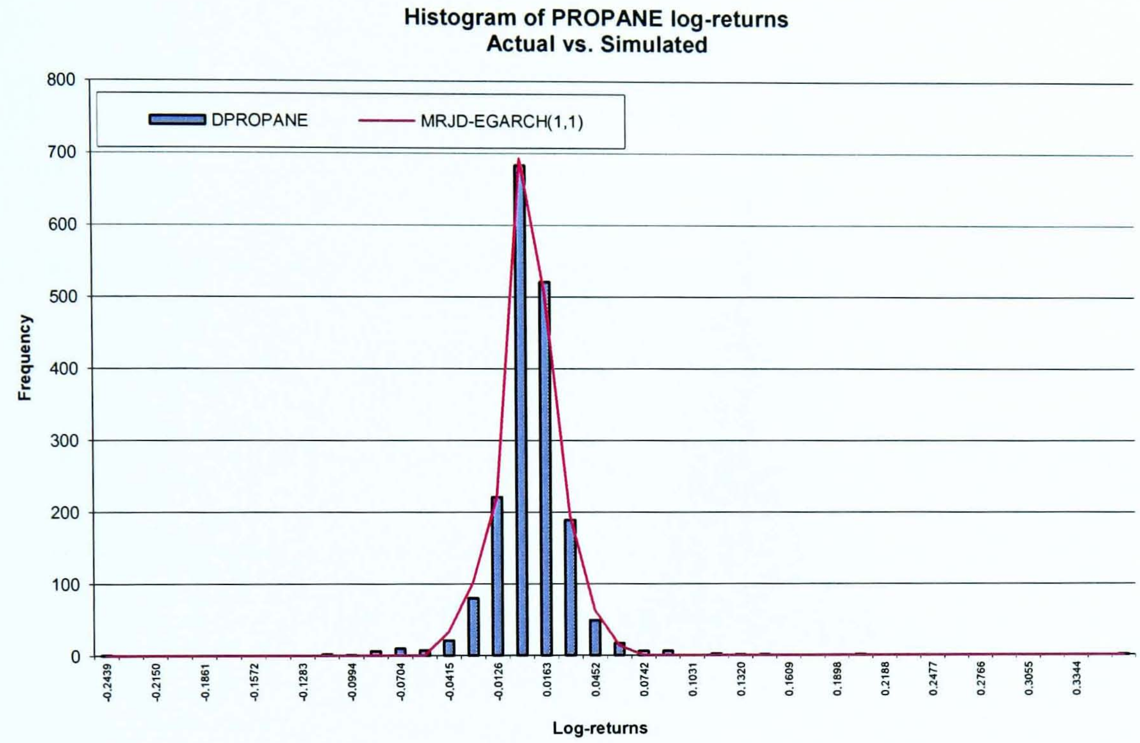
Panel D: 1-1 Crack Spread of Heating Oil with WTI (CS-HO-WTI)



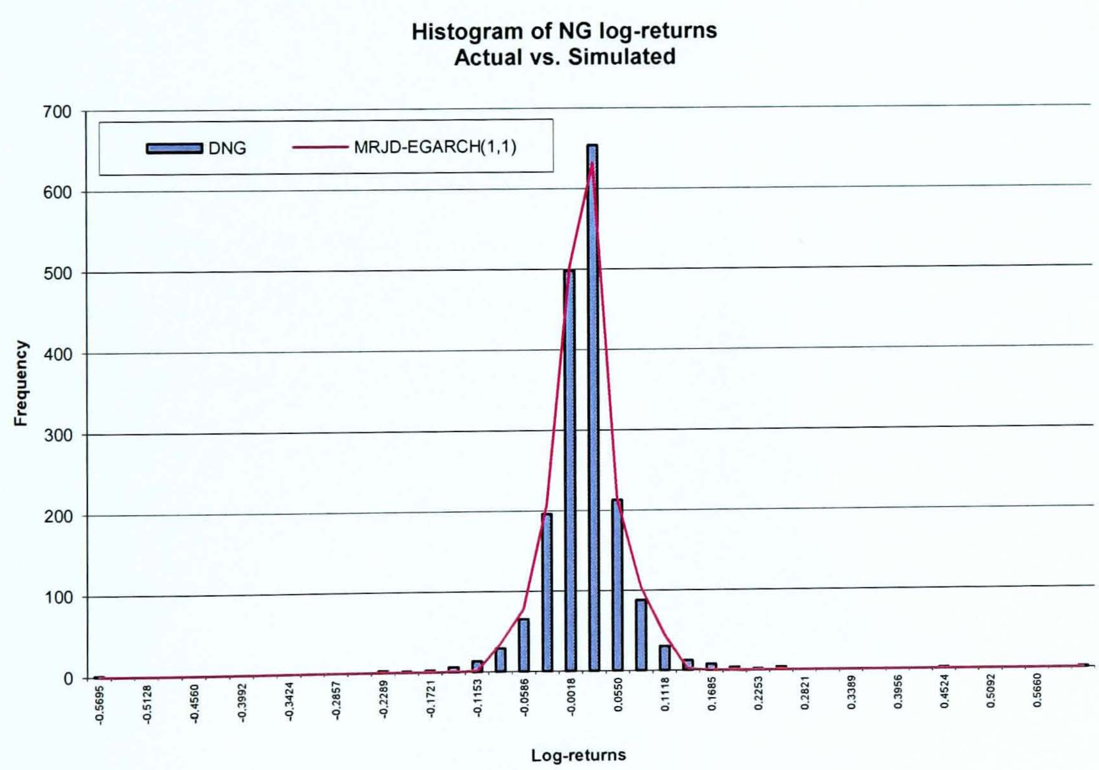
Panel E: 1-1 Crack Spread of Gasoline with WTI (CS-Gasoline-WTI)



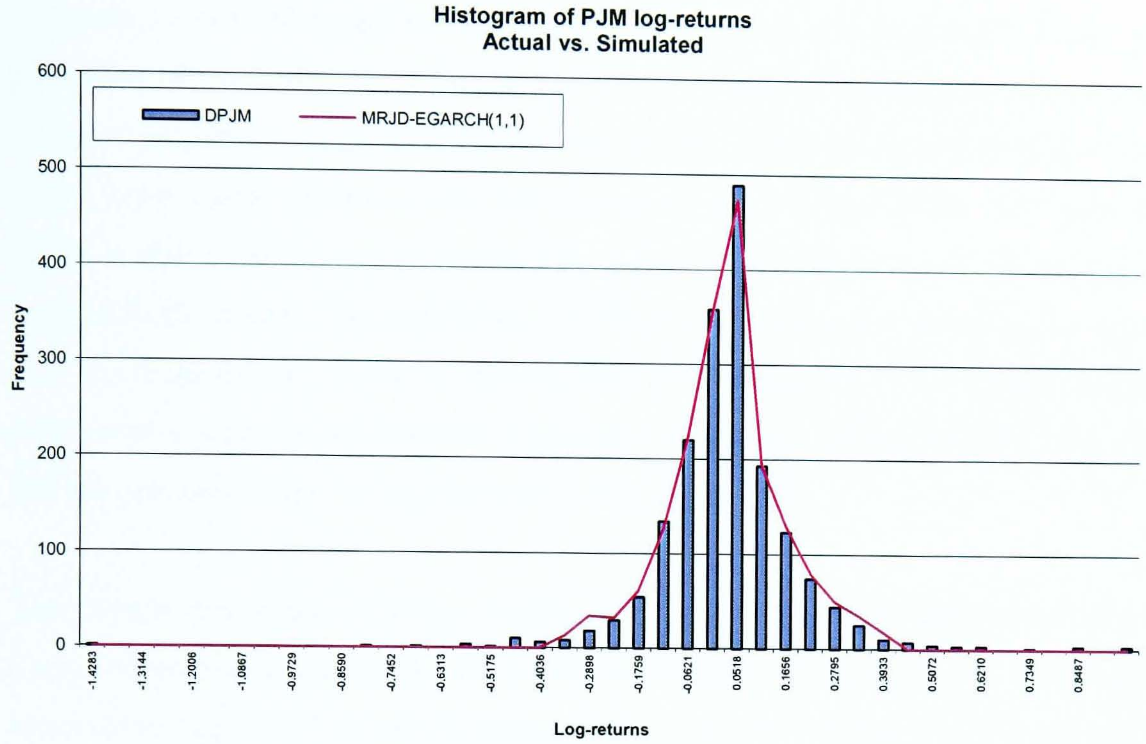
Panel F: Propane - Mont Belvieu Texas (Propane)



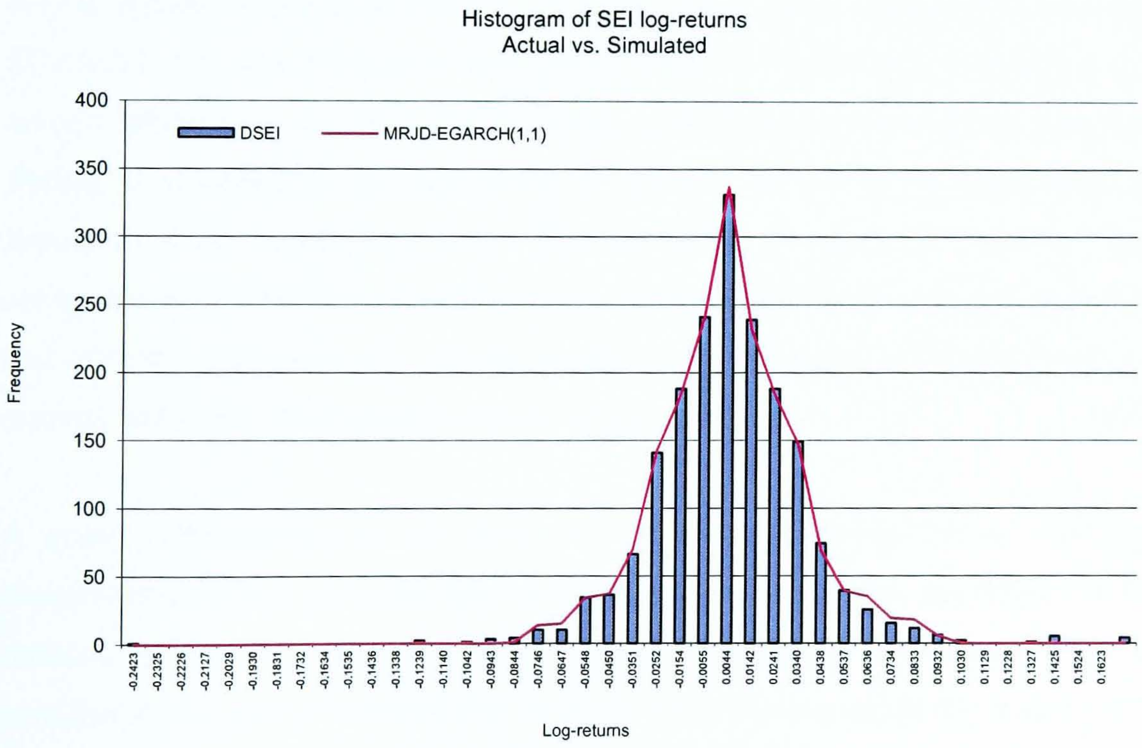
Panel G: Natural Gas - Henry Hub (NG)



Panel H: Interconnection Electricity Firm On Peak Price Index (PJM)



Panel I: Spot Energy Index (SEI)



3.6. Conclusions

In this chapter the behaviour of spot prices in the eight energy markets that trade futures contracts on NYMEX and the constructed energy index is examined. Given the stylised properties of these markets, a mean-reverting spike model is proposed that incorporates two different speeds of mean reversion to capture the fast mean-reverting behaviour of prices after a jump occurs and the slower mean reversion rate of the diffusive part of the model. The model is also extended to incorporate time-varying volatility in its specification, modelled as an EGARCH process. The estimation results from the historical series indicate the presence of a "leverage effect" for WTI, Heating Oil, and Heating Oil – WTI crack spread spot log-price returns, whereas for Gasoline, Gasoline – WTI crack spread, NG, Propane, PJM and the SEI the presence of an "inverse leverage" effect is found.

The comparison of the different models used in this chapter is done using 100,000 Monte Carlo simulations in each case. The results indicate that the inclusion of Poisson jumps to the mean reverting model, in combination with the use of a different speed of mean reversion after a jump occurs, for a duration equal to the half-life of the jumps' returns, improves the fit significantly for all energy markets and the SEI. The proposed modelling approach captures very well both the skewness and kurtosis of the actual series. Furthermore, the addition of the EGARCH (1,1) specification for the variance improves the fit of the simulated returns to the actual distributions, for most of the energy markets under investigation and the SEI. This finding is validated by the reported K-S statistics, as well as by comparing visually the simulated to the actual price series. Hence, overall, the proposed modelling approach for energy pricing combined with the findings of this chapter is relevant for both policymakers and market participants as it can be applied for forecasting, risk management, derivatives pricing, and policy development and monitoring purposes.

A sound understanding of the stochastic dynamics of energy prices, with their unique characteristics which make the risk management ideas and models developed for the financial markets, not directly applicable to the energy complex, is a prerequisite for making an investment into energy commodities. In today's fast moving and at the same time risk loaded energy trading environments, managing risk effectively is a critical success factor for any trading business and of outmost importance for the development of the fast-growing energy derivatives and ETFs markets. The lack of good risk management practices can often turn out to be very costly for the participants in the energy markets. Thus, with increased management calls for a simple risk measurement that would be easy to interpret, a single number as represented by Value-at-Risk, has recently dominated as the most suitable risk management tool.

The risk management models and framework proposed in the next chapter move towards this direction by optimally capturing the behaviour of the energy markets under investigation, accounting not only for their frequency of occurrence but also for the volatility spikes and their clustering behaviour through time. An innovative VaR methodology to manage spot price risk of the individual energy commodities and the constructed spot energy index is proposed. Among a number of traditional and the proposed VaR models, the best set of models appropriate to capture the dynamics of the energy prices and the SEI is selected, assessing their performance while quantifying energy price risk by calculating both VaR and ES measures. A consistent risk management framework and improved methods are required for measuring and modelling tail risk, while at the same time effectively assessing the integrity of the models.

Chapter 4.

4. Risk management in the energy markets and Value-at-Risk modelling: a hybrid approach

This chapter proposes a set of VaR models appropriate to capture the dynamics of energy prices and subsequently quantify energy price risk by calculating VaR and ES measures. Amongst the competing VaR methodologies evaluated in this paper, besides the commonly used benchmark models, a MC simulation approach and a Hybrid MC with Historical Simulation approach, both assuming various processes for the underlying spot prices, are also being employed. All VaR models are empirically tested on eight spot energy commodities that trade futures contracts on NYMEX and the Spot Energy Index. A two-stage evaluation and selection process is applied, combining statistical and economic measures, to choose amongst the competing VaR models. Finally, both long and short trading positions are considered as it is extremely important for energy traders and risk managers to be able to capture efficiently the characteristics of both tails of the distributions.

4.1. Introduction

The events and especially the aftershocks of the recent financial crisis have been unprecedented, at least in terms of the speed and magnitude of the shock, and the potential long-term impact on the global real economy. As Rogoff and Reinhart (2008) point out, most of the 18 major banking crises and a number of more minor crises that they recorded since World War II, with a major market event appearing at least every 10 years, were caused by excess liquidity in the economy along with a general misjudgement on the benefits of a certain type of innovation. The recent financial crisis of 2007 was no different. Financial innovation in the form of sophisticated securitized instruments contributed to a false sense of security around systemic risk reduction, while at the same time excess liquidity was pouring into the developed countries' financial and housing markets, mostly by investments coming from the emerging markets.

The latest economic recession and its subsequent shock waves significantly affected international trade, the commodity markets and most specifically the energy markets. Oil markets rallied upwards for almost a year after the crisis started, peaking at $145 per barrel, then suddenly collapsed to $31 per barrel within a few months, quickly then recovering some of the lost ground, trading above $60 per barrel until now. These recent energy markets' dynamics can be attributed not only to the prevailing supply and demand conditions, but also to the growth of speculative investments by a more diverse and sophisticated body of market players, including investment banks, hedge funds, pension funds, Exchange Traded Funds (ETFs) and Exchange Traded Notes (ETNs) that follow the commodity markets. This increased sophistication and analytical skills that were brought in to the energy markets, made the use of forecasting models, hedging tools, and risk management techniques, and thus in extension the VaR applications, essential tools for quantifying energy price risk. In this newly created energy environment, precise monitoring and protection against market risk has become a necessity. Power utilities, refineries or any other energy market player can use valuable information derived from the VaR exercise applied in-house, to plan and implement their future risk management strategy.

Following the amendment of the Basel Capital Accord by the Basel Committee on Banking Supervision in 1998, that obliged all member banks to calculate their capital reserve on the basis of VaR, the VaR measurement has become extremely popular both with practitioners as well as academics. As a result, numerous methods have been developed for calculating VaR, proposing techniques that have been significantly refined from the initially adopted Risk Metrics (JP Morgan, 1996), with the goal of providing reliable estimates (Jorion, 2006). The aim of this chapter is to investigate whether the widely used in the financial world Value-At-Risk (VAR) and Expected Shortfall (ES) methodologies, along with a new set of proposed models, can be successfully applied in the energy sector. VaR is used to identify the maximum potential loss over a chosen period of time, whereas the ES measures the difference between the actual and the expected loss when a VaR violation occurs.

Although a large body of the empirical literature is focused on forecasting energy prices and their volatilities, according to Aloui and Mabrouk (2010) they are far from finding any consensus about the appropriate VaR model for energy price risk forecasting. This chapter attempts to close this gap in the existing literature by proposing a set of models appropriate to capture the dynamics of energy prices and subsequently quantify energy price risk by calculating VaR and ES measures. The methodologies employed include standard VaR approaches like the Risk Metrics, GARCH and many other commonly used models, MC simulations, and a hybrid Monte Carlo with Historical Simulations introduced for the first time in this paper (to the best of the author's knowledge). The model specifications for the MC simulations and the hybrid approach are the MR and MRJD models, modified to allow for GARCH and EGARCH volatility, and for different speeds of mean reversion after a jump is identified, as described in chapter three.

Simulation models are widely used in VaR applications since they help in understanding any potential risks in an investment decision, and in preparing for the possibility of a catastrophic outcome even though it might have a small probability of occurring. There are a number of recently proposed simulation methods for generating reliable VaR estimates due to the flexibility they offer. Huang (2010) proposes a Monte Carlo Simulation VaR model that accommodates recent market conditions in a general manner. By applying the methodology on the S&P 500 returns he finds that the VaR estimation via the proposed optimization process is reliable and consistent, producing better back-testing outcomes for all out-of-sample periods tested. By simulating the value of an asset under a variety of scenarios not only the possibility of falling below the desirable level can be identified, but there can also be measures taken to prevent this event from occurring in the future.

This chapter employs a two-stage evaluation and selection process, combining statistical and economic measures, to choose between numerous competing VaR models applied in a number of energy commodities and the Spot Energy Index. The proposed SEI can be closely monitored by the major players of the energy industry and used as the underlying asset to many derivatives products such as futures and forwards, options, swaps, and also as the underlying index of energy ETFs, ETNs, and hedge funds. Amongst the competing VaR methodologies evaluated in this chapter, besides the commonly used benchmark models, a MC simulation approach and a Hybrid MC with Historical Simulation approach, both assuming various processes for the underlying spot prices, are also being proposed.

In contrast to most existing studies on VaR modelling that consider only long positions, this chapter examines both long and short trading positions. It is extremely important for energy traders and risk managers to know whether the models they are using can capture efficiently the characteristics of both tails of the distributions, as there are a lot of short players in the market alongside the long players. When taking short positions there is a risk of increasing prices, whereas when taking long positions the risk comes from falling prices. Thus, the focus should be on the left tail of the returns' distribution for the latter case, and on the right tail for the former case. Within the energy markets, the results of this chapter have important implications for the accurate risk management of energy risk and the development of the fast-growing energy derivatives and ETFs markets.

Furthermore, although the proposed VaR model selection process reduces the numerous competing models to a smaller set, in some cases more than one model is identified as the most appropriate. It is in those cases that the modeller should view the selection process as being more valuable and useful than the actual VaR number obtained, and use in combination to the proposed evaluation process other real world considerations for his/ her final choice. As Poon and Granger (2003) argue in their paper, the most important aspect of any forecasting exercise is by itself the comparison process of competing forecasting models.

The structure of this chapter is as follows. Sections 2 and 3 describe the VaR methodologies and the back-testing procedure employed, respectively. Section 4 presents the data used. Section 5 offers the empirical results of the study and, finally, section 6 concludes the chapter.

4.2. VaR Methodologies

VaR is defined as the maximum expected loss in the value of an asset or a portfolio of assets over a target horizon, subject to a specified confidence level. Thus, VaR sums up the risk which an asset or a portfolio is exposed to in a single monetary (or expected return) figure. That makes the VaR approach directly applicable to the field of energy prices. Statistically speaking, the calculation of VaR requires the estimation of the quantiles of the distribution of returns and can be applied to both the left (long positions) and the right (short positions) tails. Generally, the VaR of a long position can be expressed by the following formula:

$$Pr(r_{t+1} \leq VaR^{a}_{t+1}|\Omega_t) = a \tag{4.1}$$

where, $r_{t+1}$is the return of the asset or portfolio of assets over a time horizon (in this case one day) from t to t+1, α is the confidence level, and Ω_t is the information set at time t. The VaR for a short position is computed using the same definition, with the only difference of substituting α with 1-α. The ES for a long position, defined as the average loss over the VaR violations from the N out-of-sample violations, is also expressed mathematically as:

$$ES_a = \{E[r_{t+1}|(r_{t+1} \leq -VaR_{t+1}(a))] \tag{4.2}$$

As far as the energy markets are concerned, there has been a recent increase in the relevant empirical literature on testing VaR models and assessing their performance. These papers include a wide range of models from the standard Variance Covariance, to Historical Simulation variations, Monte Carlo simulation, and a plethora of models of the ARCH-type, also including long memory variations, under different distributional assumptions for the returns' innovation (see among others, Chiu et al., 2010; Aloui and Mabrouk, 2010; Huang et al., 2008; Sadeghi and Shavvalpour, 2006; Giot and Laurent, 2003; Cabedo and Moya, 2003). Moreover, there have also been a few studies estimating VaR on the energy markets using an extreme value theory approach (see among others, Nomikos and Pouliasis, 2011; Marimoutou et al., 2009; Krehbiel and Adkins, 2005). Results however, are contradictory in terms of the accuracy of the VaR models proposed, with plenty of discussions focusing on as to whether the simpler models can outperform the more complex/ flexible ones. Brooks and Persand (2003) find that simple models achieve comparably better VaR forecasts to the more complex ones, while Mittnik and Paolella (2000) show that more accurate VaR forecasts can be achieved with the more flexible models. In addition, Bams et al. (2005) find that amongst the models they examine, the simple models often lead to underestimation of the VaR, whereas the opposite holds for the more complex models that seem to lead to overestimation of the VaR.

Furthermore, following the emerging concept in the literature of combining VaR forecasts, Chiu at al. (2010) propose a composite VaR model to increase forecast effectiveness. In the same lines, Hibon and Evgeniou (2005) suggest that by combining forecasts instead of selecting an individual forecasting model, modelling risk is reduced. Choosing the most suitable VaR model for each commodity and for the SEI is of outmost importance for all energy market players, traders, hedgers, regulators, and policy-makers as modelling risk is reduced, and thus avoiding faulty risk management caused by the selected model's inefficiencies.

In principle, there are three general approaches to compute VaR, each one with numerous variations. The first one is to assume the return distributions for the market risks. The second one is to use the variances and co-variances across the market risks, and the third one is to run hypothetical portfolios through historical data or by using Monte Carlo simulations. Within these three general approaches to VaR, there are many different methodologies available, supported mostly by the internal model's approach that gives banks and investment houses the freedom to choose or develop their own methodology.

This chapter describes various models originating from all three approaches, and compares their performance for accurately calculating VaR for the energy commodity markets. Considering that the proposed MC simulation models jointly take into account two sources of uncertainty, jumps and high volatility with both having some predictable component, the VaR estimates from the proposed specifications are compared to those obtained with more established methods, like the RiskMetrics or Historical Simulation methods. In addition, a Hybrid approach for calculating VaR is developed based on a combination of both the MC Simulations and the Historical Simulation methodologies. Table 4-1 (panels A to D) summarizes all the VaR models compared in this chapter, in total twenty two. All the models listed under panels A and B are variance forecasting models with their sole focus on forecasting tomorrow's volatility. Panels C and D list all the proposed Monte Carlo simulation and Hybrid Monte Carlo – Historical Simulation models. Thus, the major difference between all aforementioned the models lies with the methodology used to calculate volatility. The methodology, the main properties and the underlying distribution used in each model, both the more established and the proposed ones are all explained in more detail in the subsequent sections.

Table 4-1: VaR models compared.

List of all Value-at-Risk models compared. "V&C" stands for Variance & Covariance; "RM" for Risk Metrics; "HS" for Historical Simulation; "F-HS" for Filtered Historical Simulation; "MCS" for Monte Carlo Simulation; "HMCS" for Hybrid Monte Carlo Simulation; "GBM" for Geometric Brownian Motion; "MR" for Mean Reversion; "MRJD" for Mean Reversion Jump Diffusion; "OLS" for Ordinary Least Squares (constant volatility); "GARCH" for Generalised Autoregressive Conditional Heteroscedasticity; "F-GARCH" for Filtered GARCH; "EGARCH" for Exponential GARCH; "F-EGARCH" for Filtered EGARCH.

Panel A: Commonly used	**Panel B: ARCH-type**
V&C	GARCH
RM	F-GARCH
HS	EGARCH
F-HS	F-EGARCH
Panel C: MC Simulation	**Panel D: Hybrid MC-HS**
MCS-GBM	HMCS-GBM
MCS-MR-OLS	HMCS-MR-OLS
MCS-MR-GARCH	HMCS-MR-GARCH
MCS-MR-EGARCH	HMCS-MR-EGARCH
MCS-MRJD-OLS	HMCS-MRJD-OLS
MCS-MRJD-GARCH	HMCS-MRJD-GARCH
MCS-MRJD-EGARCH	HMCS-MRJD-EGARCH

4.2.1. Variance-Covariance Model

The Variance-Covariance (V&C) method is a widely used method of computing VaR due to its simplicity and computational efficiency. However, it has a major drawback as it assumes that returns are normally distributed; a rather unrealistic assumption for the energy markets that are characterised by fat-tailed return distributions. Within the family of V&C methods there are several methodologies that can be used to calculate the VaR, based on the way the forecasted variance is calculated. For the purposes of this thesis the equally weighted Moving Average (MA) methodology is used, which assumes that future variance can be estimated from a pre-specified window of historical data, weighing equally all the historical observations used. The equally weighted MA model is expressed as:

$$\sigma_t = \sqrt{\frac{1}{(k-1)} \sum_{s=t-k}^{t-1} r_s^2} \tag{4.3}$$

where, t is the estimation date of the standard deviation of returns over a time window from date t-k to t-1.

4.2.2. RiskMetrics

RiskMetrics (RM) is an Exponentially Weighted Moving Average (EWMA) VaR measure assuming that the standardised returns (returns over the forecasted standard deviation) are normally distributed (JP Morgan, 1996). The RM methodology focuses on the size of the returns but only relative to their standard deviation. A large return, irrespective of the direction, during a period of high volatility could lead to a low standardised return, whereas during a low volatility period it could result to an abnormally high standardised return. This standardization process leads to a more accurate VaR computation as large outliers are considered more frequent than would be expected with a normal distribution. The unconditional standard deviation of the RM model is expressed as:

$$\sigma_t = \sqrt{(1-\lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2};\ \lambda \in (0,1) \tag{4.4}$$

where λ is the decay factor, reflecting how the impact of past observations decays while forecasting one-day ahead volatilities. The more recent the observation the largest the impact, with an exponential decay effect as observations move more into the past. The highest (lowest) the value for λ is, the longer (shorter) the memory of past observations is. The value of 0.94 is assigned for λ which is widely used in the literature.

4.2.3. ARCH Models

ARCH (autoregressive conditional heteroscedasticity) models of volatility, initially proposed by Engle (1982), are commonly used by researchers and practitioners to calculate the VaR of their portfolios. Amongst the most popular ARCH formulations used are the GARCH (Bollersev, 1986) and EGARCH (Nelson, 1991) volatility models, because of their ability to capture many of the typical stylised facts of both financial and commodity time series, such as time-varying volatility, persistence, and volatility clustering. According to Engle (2001), models that explicitly allow for the standard deviation to change over time, thus allowing for heteroskedasticity, perform better in forecasting the variance, and thus by extension, in measuring the VaR. Giot and Laurent (2003) and Kuester et al. (2006) conclude that VaR can be captured more accurately using GARCH-type models instead of using non-parametric ones. A key advantage of the GARCH and EGARCH models in terms of calculating VaR is that, according to Christoffersen (2003), the one-day forecast of the variance$\sigma^2_{t+1|t}$, is given directly from the model as σ^2_{t+1}, which is the conditional volatility following respectively a GARCH or an EGARCH process. A more detailed explanation is given in the following sections.

4.2.3.1GARCH & Filtered GARCH

Under the GARCH volatility specification the return series is assumed to be conditionally normally distributed, with the VaR measures being calculated by multiplying the conditional standard deviation by the appropriate percentile point on the normal distribution, following Sarma et al. (2003). The conditional volatility following a GARCH(1,1) process is expressed as:

$$\sigma_t = \sqrt{\beta_0 + \beta_1 \varepsilon^2_{t-1} + \beta_2 \sigma^2_{t-1}} \tag{4.5}$$

where, β_0, β_1, and β_2 are positive constants, with $\beta_1 + \beta_2 < 1$expressing the "non-explosivity" condition, ε^2_{t-1} representing the previous periods' return innovations, and σ^2_{t-1} being the last period's forecast variance (GARCH term). Once σ_t is forecasted, the VaR estimates are obtained using the relevant percentile points on the normal distribution for the 99% and 95% VaR, under both long and short positions. Daily volatility forecasts are computed using a rolling estimation window of 1827 daily observations each. The process is then rolled forward until all the data is exhausted[19].

Next, the VaR based on the Filtered GARCH (F-GARCH) process is also calculated. The term filtered refers to the fact that instead of using directly the forecasted variance from the GARCH model, a set of shocks z_i is used, as explained below, which are returns filtered by the forecasted variance . The VaR is estimated from the empirical percentile, which is based on observed information, using the following mathematical expression:

[19] The starting coefficients for the GARCH models are obtained from the Yule-Walker equations, and the log-likelihood function is maximized using the Marquardt optimization algorithm.

$$VaR_{t+1} = \hat{\sigma}_{GARCH_{t+1}} Percentile\{(z_i)_{i=t-T}^{t}, a\}; T = 1827\ days \qquad (4.6)$$

where $z_i = r_i/\hat{\sigma}_{GARCH_{t+1}}$ are the standardised residuals and $\hat{\sigma}_{GARCH_{t+1}}$ is the forecasted GARCH volatility using an estimation sample window of width $T = 1827$ days.

4.2.3.2 EGARCH & Filtered EGARCH

To cope with the skewness commonly observed in commodities markets, and to capture the potential presence of an "inverse leverage" effect[20], the more flexible model of persistence, the Exponential GARCH (EGARCH) model is used, which is expressed as:

$$\sigma_t = \sqrt{e^{\beta_0 + \beta_1 * \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \beta_2 * \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_3 * \ln\left(\sigma_{t-1}^2\right)}} \qquad (4.7)$$

where, β_0 denotes the mean of the volatility equation. The coefficients β_1 and β_2 measure the response of conditional volatility to the magnitude and the sign of the lagged standardised return innovations, respectively; as such, these coefficients measure the asymmetric response of the conditional variance to the lagged return innovations. When $\beta_2 = 0$, there is no asymmetric effect of the past shocks on the current variance, while when $\beta_2 \neq 0$ asymmetric effects are present in response to a shock; for instance, $\beta_2 > 0$ indicates the presence of an "inverse leverage" effect. Finally, β_3 measures the degree of volatility persistence.

As in the case with the GARCH model, the Filtered EGARCH (F-EGARCH) process is also calculated. Again, the term filtered refers to the fact that a set of returns filtered by the forecasted EGARCH variance is used. The VaR is estimated using the following mathematical expression:

$$VaR_{t+1} = \hat{\sigma}_{EGARCH_{t+1}} Percentile\{(z_i)_{i=t-T}^{t}, a\}; T = 1827\ days \qquad (4.\ 8)$$

where $z_i = r_i/\hat{\sigma}_{EGARCH_{t+1}}$ are the standardised residuals and $\hat{\sigma}_{EGARCH}$ is the forecasted EGARCH volatility using as estimation sample window of width $T = 1827$ days.

[20] Financial markets tend to exhibit a negative correlation between volatility and price, an effect known as "leverage", with negative shocks having a greater impact on volatility compared to positive ones.

4.2.4. Monte Carlo Simulation

Another popular method for estimating VaR is Monte Carlo simulation which is based on the assumption that prices follow a certain stochastic process (GBM, JD, MR-JD etc.), and thus by simulating these processes one can yield the distribution of the asset's value for the predetermined period. By simulating jointly the behaviour of all relevant market variables to generate possible future values, the MC simulations method allows for the incorporation of future events affecting the market as well as the additions of jumps or extreme events, thus accurately modelling the market's behaviour. In VaR applications, the required quantile for both the left and the right tails can be obtained directly from the random paths. MC simulation is a powerful tool for energy risk management that owes its increased popularity to its flexibility. It can incorporate in the modelling procedure all the important characteristics of the energy markets' behaviour such as seasonality, fat tails, skewness and kurtosis, and is also able to capture both local and non-local price movements. It is mostly due to this flexibility that Duffie and Pan (1997), and So et al. (2008) conclude that the MC approach is probably the best VaR methodology. The only troubling issue with the MC approach is the fact that it is relative complex to implement, and that it can be computationally demanding.

With the MC simulations method the VaR of an asset or a portfolio is quantified as the maximum loss in the random variables distribution, associated with the appropriate percentile. In order to calculate the VaR, first the dynamics of the underlying processes i.e. prices, volatilities etc. need to be specified. Second, N sample paths need to be generated by sampling changes in the value of the asset or individual assets that comprise a portfolio (risk factors), over the desired holding period. Third, all information enclosed in the probability distribution needs to be incorporated. Fourth, using the N sample paths the value of each underlying risk factor needs to be determined, given the assumed process for each one. Finally, the individual values need to be used to determine the value of the asset/ portfolio at the end of the holding period.

The following seven specifications are used for modelling the spot prices of the energy markets examined:

1. Geometric Brownian Motion (GBM)
2. Mean Reversion with Ordinary Least Squares (constant) volatility (MR-OLS)
3. Mean Reversion with GARCH(1,1) volatility (MR-GARCH(1,1))

4. Mean Reversion with EGARCH(1,1) volatility (MR-EGARCH(1,1))
5. Mean Reversion with Jump Diffusion and OLS volatility (MRJD-OLS)
6. Mean Reversion with Jump Diffusion and GARCH(1,1) volatility (MRJD-GARCH(1,1))
7. Mean Reversion with Jump Diffusion and EGARCH(1,1) volatility (MRJD-EGARCH(1,1))

A detailed explanation of these models can be found in section 2 of chapter 3. As with other VaR methodologies, any modifications to the MC simulations approach focus mostly on using various techniques to reduce computational burden. For example, Jamshidan and Zhu (1997) use principal component analysis to narrow down the number of factors used into the simulation process, a procedure they name scenario simulations. Glasserman et al. (2000), guide the MC simulations sampling process using approximations from the V&C approach, resulting in time and resources savings without the loss of precision. The MC simulation along with the hybrid MC-HS methodologies proposed in this thesis for estimating the VaR of energy commodities and the SEI are a significant improvement of existing ones due to their flexibility. They allow for any stochastic process to be used for describing the distribution of returns, and at the same time allow for the incorporation in the model of all major features that define the behaviour of energy prices. Such features include seasonality, time varying volatility, volatility clustering, mean reversion, jumps, and most importantly a different speed of mean reversion after a jump occurs.

For estimating all inputs for the MC simulations 1,827 daily observations from the in-sample period are used. Using each time the relevant underlying process 100,000 simulations are run, forecasting the spot prices 623 days ahead. Then, using the average simulated path the daily VaR for each one of the 623 forecasted returns is estimated. The mathematical expression for calculating the VaR using the MC Simulation models is the following:

$$VaR_t = Percentile\{r_t^s, a\} \tag{4.9}$$

where r_t^s is the total number of simulated returns at time t.

4.2.5. Historical Simulation & Filtered Historical Simulation

The historical simulation (HS) method is amongst the simplest ones for estimating the VaR for various assets and portfolios. HS uses the past history of returns to generate the distribution of possible future returns; in contrast to MC simulation which follows a certain stochastic process. In addition, the time series data used to run the HS are not used to estimate future variances and covariances, as is the case in the V&C approach; the assets returns over the time period examined provide all necessary information for computing the VaR. As with other methodologies for calculating VaR, there are various modifications of the HS method suggested, such as weighing the recent past more (Boudoukh et al., 1998), combining the HS with various time series models (Cabedo and Moya, 2003), and updating historical data for shifts in volatility (Hull and White, 1998).

Under the HS methodology, the VaR with coverage rate, a, is then calculated as the relevant percentile of the sequence of past returns, obtained non-parametrically from the data. The mathematical expression of the one-day-ahead VaR using the HS method is the following:

$$VaR_{t+1} = Percentile\left\{\{r_i\}_{i=t-T}^{t}, a\right\};\ T = 1827 \text{ days} \tag{4.10}$$

where T is the window width of past observations used. The window width of historical data used in the estimations plays a crucial role in the efficiency of the HS methodology. Having sufficient history of the relevant returns makes the HS method very attractive to use, mostly due to its simplicity, intuitive and straight forward implementation, and also its wide applicability to all instruments and market risk types. The HS method takes into account fat tails and skewness as it is based on past historical data. One of the method's drawbacks is that it is computationally demanding, and also the fact that the assumed returns distribution is based on the historical distribution over the time period selected, which can lead to significant variations in the VaR estimate when different time periods are used. This becomes even more important for the energy markets where risks are volatile and of big magnitude, and structural shifts occur at regular intervals.

Following, the VaR based on the Filtered Historical Simulation (FHS) is also calculated, using the following mathematical expression:

$$VaR_{t+1} = \sigma_i Percentile\left\{\{z_i\}_{i=t-T}^{t}, a\right\};\ T = 1827 \text{ days} \tag{4.11}$$

where $z_i = r_i / \sigma_i$ are the standardised residuals and σ_i is the volatility of the 1827 historical observation window. The term filtered refers to the fact that the raw returns are not used to simulate, but instead a set of return shocks z_i, which are the returns filtered by the historical volatility of a window width T, are used. Thus, the FHS is a combination of the non-parametric HS and a parametric model. This combination is more likely to improve the HS VaR estimates as it continues to accommodate the dynamics of the empirical distribution, such as skewness, fat tails and volatility clustering. Also, the FHS method has the advantage that no assumptions need to be made for the distribution of the return shocks, and offers the flexibility of allowing the computation of any risk measure and for any investment horizon. Finally, one of the disadvantages that both the HS and FHS methods share is that each observation in the time series used for the simulation carries an equal weight for measuring VaR, which can be a problem when there is a trend identified in the series.

4.2.6. Hybrid Monte Carlo - Historical Simulation

The Hybrid MC-HS approach developed in this thesis can be the most appropriate methodology for calculating the VaR in the energy markets as it combines all the advantages of using two of the most popular and efficient existing methods, the MC simulations and the Historical Simulation. The HS methodology and all the proposed variations in the literature are mostly designed to capture any shifts in the recent past that are usually underweighted by the conventional approach. All of these proposed variations fail to bring in the risks that are not already included in the sampled historical period or to capture any structural shifts in the economy and the specific market examined. In contrast, the Hybrid MC-HS approach gives an accurate picture of the asset's risk as it allows for the incorporation of jumps and fat-tails in the returns' distribution, due to the flexibility provided by the MC simulations.

Both, the MC simulations and the Historical Simulation approaches are very popular amongst practitioners for calculating the VaR of their portfolios because of their flexibility, ease of use, and estimation performance. Perignon and Smith (2010) find that amongst the banks in their global sample that disclose their VaR methodology, 73% use the HS methodology or any of its variations, whereas the MC simulations methodology is the second most frequently applied VaR method, used by 22% of the banks. As mentioned previously, there have been many variations proposed in the literature for the MC simulations and the HS approaches, but only looking at each approach separately. However, to the best of our knowledge, is the first time that the MC simulation approach is combined with the HS in order to produce a Hybrid approach for calculating the VaR of energy assets.

Zikovic and Filer (2009) introduce a hybrid approach based on a combination of nonparametric bootstrapping and parametric GARCH volatility forecasting. They test the model using daily returns from sixteen market indexes, half from developed and the other half from emerging markets. The authors find that only the proposed hybrid model and the EVT-based VaR models can provide adequate protection in both developed and emerging markets. Lambadiaris et al. (2003) calculate the VaR in the Greek bond and stock markets using separately the HS and MC simulations approaches, and they find that for the linear stock portfolios the MC simulations approach performed better, as the HS approach overstated the VaR, whereas in the case of the non-linear bond portfolios the results are mixed. Vlaar (2000) investigates the Dutch interest rates term structure and applies the historical simulation, variance-covariance, and Monte Carlo simulation methods for estimating the accuracy of the VaR. He finds that the best results are obtained for a combined variance-covariance MC method that uses a term structure model with a normal distribution and a GARCH specification. Moreover, Hendricks (1996) compares the VaR estimates from the V&C and HS approaches, applied on foreign exchange portfolios, and concludes that both approaches have difficulties in capturing extreme outcomes and shifts in the underlying risks. Thus, it can be argued that in case of computing the VaR for non-linear assets over long time periods, where data are more volatile, with the non-stationarity and the normality assumptions being debatable, the MC simulations approach performs better than the HS approach.

Using each time the relevant underlying process 100,000 simulations are run, forecasting the spot prices 623 days ahead[21]. Then, using the average simulated path, the daily VaR is estimated using a 1 day ahead rolling window method as it is the case with the HS method. The estimation window is the first 1,827 daily forecasts, rolled one step forward for the next 623 days. The mathematical expression for calculating the VaR using the Hybrid model is the following:

[21] For estimating the inputs for the MC simulations all 2,450 daily observations from the sample are used.

$$VaR_{t+1} = Percentile\left\{\left\{\overline{r}_i\right\}_{i=t-T}^{t}, a\right\};\ T = 1827 \text{ days} \tag{4.12}$$

where $\overline{r}_t^s = \sum_{\omega=1}^{n} \frac{r_{t,\omega}^s}{n}$ is the average per time-step simulated return at time t, $r_{t,\omega}$ is the return of the simulated spot price of path ω at time t, n is the number of MC simulations, and T is the estimation window of 1827 observations.

4.3. VaR Back-testing procedure

Having presented previously the various risk management techniques, this section sets forth a model selection process including all aforementioned models despite the major drawbacks and obvious limitations that some may have. This is done because it is expected that the tests of VaR models used, and the selection process proposed, will effectively reject the weakest models, knowing that some of them are widely used in practice. That makes the results of this chapter even more important as useful feedback will be provided about the models' quality and efficiency.

To select the best model in terms of its VaR forecasting power, a two stage evaluation framework is implemented. In the first stage, three statistical criteria are used to test for unconditional coverage, independence, and conditional coverage, as proposed by Christoffersen (1998). A VaR model successfully passes the first stage evaluation only when it can satisfy all three statistical tests, at the 5% or higher significance level. In the second stage, a loss function is constructed in line with Lopez (1999) and Sarma et al. (2003) to test the economic accuracy of the VaR models that have passed the first evaluation stage. Then, the model that delivers that lowest loss function value is compared pair-wise with all remaining models that have passed the first evaluation stage, using the modified Diebold-Mariano (MDM) test as proposed by Harvey et al. (1997). Thus, the benchmark model is tested against the remaining models to choose the VaR calculation methodology which generates the least loss for each energy market. In general, it is worth noting that when choosing between VaR models the modeller should view the selection process as being more valuable and useful than the actual VaR number obtained.

To perform the proposed back-testing procedure a long period of historical data needs to be used. According to Alexander (2008), about 10 years of daily frequency data are needed for the results to be more powerful and to be able to reject any inaccurate VaR models. In this chapter, 2,450 daily observations are used, representing almost 10 years of history of which 1,827 are used as the in-sample (estimation sample) and 623 as the out-of-sample period. Then, using the rolling window approach, the estimation sample is rolled over the entire data period, for a fixed length of 1 day as the risk horizon.

4.3.1. Statistical evaluation

Statistical tests are used to back-test risk management models and access how well they can capture the frequency, independence, and magnitude of exceptions, defined as losses (gains) that exceed the VaR estimates. Most of these tests rely on the assumption that the daily returns are generated by an i.i.d. Bernoulli process. Thus, the "hit sequence" or "failure process" of VaR violations is defined using an indicator function $I_{a,t}$ as:

$$I_{a,t+1} = \begin{cases} \begin{cases} 1, if\ r_{t+1} < VaR_{a,t+1} \\ 0, otherwise \end{cases} ; \text{for long positions} \\ \begin{cases} 1, if\ r_{t+1} > VaR_{a,t+1} \\ 0, otherwise \end{cases} ; \text{for short positions} \end{cases} \tag{4.13}$$

where r_{t+1} is the realised daily return from time t, when the VaR estimate is made, to time t+1. The hit sequence returns a 1 on a day t+1 if the loss on that day is larger than the VaR number forecasted. If there is no violation then the hit sequence returns a 0. In order to statistically back-test the VaR models, a sequence of $\{I_{t+1}\}_{t=1}^{T}$ across T needs to be constructed, indicating the past violations. In a sample with n observations, if the "hit" series $I_{a,t}$ follows an i.i.d. Bernoulli process, an accurate VaR model should return a number of "hits" equal to $n * a$.

Then, based on this hit sequence the VaR evaluation framework, as developed by Christoffersen (1998), is applied. Three tests for unconditional coverage, independence, and conditional coverage (which combines the unconditional coverage and independence into one test) are applied on the hit sequence, using in all cases a likelihood ratio statistic. Also, the P-values associated with the test statistic are calculated, using a 5% significance level. The two types of errors associated with the significance level chosen when testing a certain hypothesis in statistics, are the Type I (rejecting a correct model) and Type II (failing to reject an incorrect model) errors. The higher the significance level is, the larger the possibility for a Type I error. Thus, in line with common practice in risk management applications, and because Type II errors can be quite costly, a high enough threshold should be imposed for accepting the validity on any VaR model, and as such a 5% significance level is chosen in this chapter[22].

First, the unconditional coverage test, introduced by Kupiec (1995) is applied, to test whether the indicator function has a constant success probability equal to the VaR significance level, a. The null hypothesis tested with LR_{UC} is that the average number of VaR violations forecasted is correct. Therefore, a VaR model is rejected in either case that underestimates or overestimates the actual VaR. The likelihood ratio statistic LR_{UC} is given by:

$$LR_{UC} = -2ln\left[\frac{(1-a)^{T_0}a^{T_1}}{(1-T_1/T)^{T_0}(T_1/T)^{T_1}}\right] \sim X^2(1) \tag{4.14}$$

where T is the out-of-sample days, T_0 *and* T_1 are the number of 0s and 1s in the sample, and χ^2 is the chi-squared distribution with one degree of freedom.

Second, the independence test is applied, to control for any clustering in the hit sequence which would indicate that the VaR model is not adequate in responding promptly to changing market conditions. The null hypothesis tested with LR_{ind} is that the VaR violations forecasted are independent. To this end, the test should be able to reject a VaR model with clustered violations. The likelihood ratio statistic LR_{ind} is given by:

$$LR_{ind} = -2ln\left[\frac{(1-T_1/T)^{T_0}(T_1/T)^{T_1}}{(1-\pi_{01})^{T_{00}}\pi_{01}{}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{11}{}^{T_{11}}}\right] \sim X^2(1) \tag{4.15}$$

where $T_{ij},\ i,j = 0,1$ is the number of observations with a j following an i. Also, π_{01} and π_{11} are given by the following equations:

$$\pi_{01} = \frac{T_{01}}{T_{00}+T_{01}} \tag{4.16}$$

[22] The smaller the significance level for the VaR estimates, the fewer the number of violations will be. Therefore, by choosing a 5% significance level more VaR violations can be observed than using a 1% level, leading to a better test for the accuracy of the VaR model.

$$\pi_{11} = \frac{T_{11}}{T_{10}+T_{11}} \tag{4.17}$$

Third, the conditional coverage test is applied, to simultaneously test whether the VaR violations are independent and that the average number of those violations is equal to n*a. The null hypothesis tested with LR_{CC} is that both the average number of VaR violations forecasted is correct, and that the VaR violations are independent. It is important to test for conditional coverage because many financial and commodity time series exhibit volatility clustering. So, VaR estimates should be narrow (wide) in times of low (high) volatility, so that VaR violations are not clustered but spread-out over the sample period. The joint test of conditional coverage can be calculated as the sum of the two individual tests, so the likelihood ratio statistic LR_{CC} is given by:

$$LR_{CC} = LR_{UC} + LR_{ind} \sim \mathcal{X}_1^2 \tag{4.18}$$

4.3.2. Economic evaluation

In the second stage of the VaR models evaluation procedure the risk manager can work with fewer models, only those that pass all three statistical tests. However, because usually more than one model pass the first evaluation stage and the risk manager cannot choose a single VaR model as the most effective, an economic evaluation framework is needed to rank the models. Lopez (1999) and Sarma et al. (2003) set-forth such an evaluation approach by creating a loss function that measures the economic accuracy of the VaR models that pass the statistical tests. In this thesis the approach introduced in Lopez (1999) and Sarma et al. (2003) is used, developing a loss function based on the notion of Expected Shortfall (ES), also termed Conditional VaR (CVaR), which measures the difference between the actual and the expected losses when actually a VaR violation occurs. A similar approach is also followed by Angelidis and Skiadopoulos (2008). Using this loss function the statistically accurate models are ranked and an economic utility function able to accommodate the risk manager's needs is specified as follows:

$$LF_i = \frac{1}{T}\sum_{j=1}^{T}\left[r_j - ES_i(a)\right]^2 \tag{4.19}$$

$$ES_a = \begin{cases} E[r_t|(r_t \le -VaR_t(a))]; \text{ for long positions} \\ E[r_t|(r_t \ge VaR_t(a))]; \text{ for short positions} \end{cases} \tag{4.20}$$

where the i_{th} ES is defined as the average loss over the VaR violations from the N out-of-sample violations that occurred for the i_{th} VaR model, under the following conditions:

$$r_j - ES_i(a) = \begin{bmatrix} \begin{cases} 0, & if\ ES_i(a) \le r_j \\ r_j - ES_i(a), & if\ r_j < ES_i(a) \end{cases} ; \text{ for long positions} \\ \begin{cases} 0, & if\ ES_i(a) \ge r_j \\ r_j - ES_i(a), & if\ r_j > ES_i(a) \end{cases} ; \text{ for short positions} \end{bmatrix} \tag{4.21}$$

The proposed LF uses the ES and not the VaR measures to compare with the actual returns, as the VaR returns do not give an indication about the size of the expected loss when a violation occurs. The model that minimizes the total loss, hence returns the lowest LF value, is preferred relative to the remaining models. Evidence in the literature shows that the ES is a more coherent risk measure than the VaR (Acerbi, 2002; Inui and Kijima, 2005). In addition, Yamai and Yoshiba (2005) argue that VaR is not as reliable as the ES measure, especially during market turmoil, and that it can be misleading for risk managers. However, the authors also suggest that the two measures should be combined for better results, as the ES estimations need to be very accurate in order to increase efficiency in the risk management process.

4.3.3. Selection process: Modified Diebold Mariano & Bootstrap Reality Check

Amongst all VaR models that passed the first evaluation stage, the model with the lowest LF, calculated during the second evaluation stage, is used as the benchmark model in order to examine whether it statistically performs better than the competing models. First, the pair-wise model comparison methodology employed is the modified Diebold Mariano (MDM) test proposed by Harvey et al. (1997). This approach overcomes the limitation of the Diebold-Mariano (1995) test of frequently rejecting the null when it is true. Then, the values of the modified DM test are compared with the critical value of the Student's t-distribution with (T-1) degrees of freedom.

The null hypothesis of the MDM test is that both the benchmark and the competing models are equally accurate in their VaR forecasts. That is,

$H_0: E(d_t) = 0$ with $d_t = LF_{1,t}^{MDM} - LF_{2,t}^{MDM}$. The MDM statistic and the loss function used to evaluate the models under this framework are the following:

$$MDM = \sqrt{\frac{T-1}{T}} \frac{\bar{d}}{\frac{\sum_{t=1}^{T}(d_t-\bar{d})^2}{T^2}} \tag{4.22}$$

$$LF_{i,t}^{MDM} = r_{i,t} - ES_{i,t} \tag{4.23}$$

where $t = 1, \ldots, T$, and $\bar{d} = \frac{\sum_{t=1}^{T} d_t}{T}$.

Second, in addition to the MDM evaluation method, to minimise the possibility that the performance amongst the competing VaR methodologies could be due to data snooping bias, the bootstrap version of White's (2000) Reality Check (RC) is implemented. According to Sullivan et al. (1999) and White (2000), data snooping occurs when a single data set is used for model selection and inference. While testing different models there is a probability of having a given set of results purely due to chance rather than these being truly based on the actual superior predictive ability of the competing models. In doing so, a relative performance measure is first constructed that can be defined as:

$$f_{k,n} = LF_{n,0} - LF_{n,k}; \quad k = 1,..,l; \ \mathrm{n} = 1,..,623 \tag{4.24}$$

where model 0 is the benchmark and k represents the k[th] model, n denotes the out-of-sample testing period, and LF is the loss function of equation (4.19) chosen in the previous section. Next, for each value of k and LF, pair wise comparisons are made between each portfolio and the remaining ones. Mathematically the null hypothesis for the reality check can be formulated as:

$$H_0 : \max_k\{E(f_k)\} \leq 0. \tag{4.25}$$

The null hypothesis states that none of the models is better than the benchmark, i.e. there is no predictive superiority over the benchmark itself. Hence, whenever the null hypothesis is accepted it means that there is no competing model that performs better in terms of its VaR forecasting ability than the benchmark model. Following White (2000), the null hypothesis is tested by obtaining the test statistic of the reality check as $T_n^{RC} = \max_k(n^{1/2}\bar{f}_k)$, where $\bar{f}_k = n^{-1}\sum_{t=1}^{n} f_{k,t}$ and n is the number of days of the out-of-sample period. To construct the test statistic, the stationary bootstrap technique of Politis and Romano (1994) is employed and B=1,000 random paths of VaR models' Loss Functions are generated. A similar approach is used by Alizadeh and Nomikos (2007) who applied the stationary bootstrap to approximate the empirical distribution of Sharpe ratios and test different trading rules in the sale and purchase market for ships.

The stationary bootstrap re-samples blocks of random length from the original data, to accommodate serial dependence, where the block length follows a geometric distribution and its mean value equals $1/q$. In this thesis, similarly to Sullivan et al. (1999)[23], $q = 0.1$ which corresponds to a mean block length of 10; for $q = 1$ the problem is reduced to the ordinary bootstrap which is suitable for series of negligible or no dependence. Finally, the bootstrap loss function and thus the performance measure, is constructed by using the simulated loss functions, whereas the Bootstrap RC p-value is obtained by comparing T_n^{RC} directly with the quantiles of the empirical distribution of T_n^{RC*} using the following expression:

$$T_n^{RC*} = \max_k\left\{n^{1/2}\left(\bar{f}_k^*(b) - \bar{f}_k\right)\right\} \tag{4.26}$$

where $\bar{f}_k^*(b)$ represents the sample mean of the relative performance measure calculated from the b^th bootstrapped sample, with $b = 1,...,B$.

With the proposed back-testing procedure, VaR forecasts can be more accurate, reducing the probability of accepting flawed models, and thus satisfying the requirements of stringent risk management control procedures. In addition, using the proposed economic utility function, the risk manager is able to rank a range of candidate VaR models and select the best performing one amongst them. Finally, the market players can be better informed, and thus well prepared to withstand any future losses, should the market moves to the opposite direction, by forecasting the ES measure more accurately.

[23] For more technical details on the implementation of the stationary bootstrap RC the reader is referred to Sullivan et al., 1999; Appendix C, pp 1689-1690.

4.4. Data

For the assessment of each VaR model examined, 2,450 daily observations in total are collected from DataStream for the period 12/09/2000 to 1/02/2010. The spot prices collected are for the eight energy markets and the Spot Energy Index analysed in the previous chapter. From the total sample, the first 1,827 observations are used in estimation to forecast the next day's VaR. Using this "rolling window" method, for a fixed length of 1 day, the estimation sample is rolled over the entire data period generating 623 daily out-of-sample VaR forecasts.

The proposed modelling approach for the energy prices and the SEI, as described in chapter 3, is a convenient tool for narrating the most important dynamics observed in the actual history of the respective spot prices. Furthermore, as it is evident from the graphs of the spot energy prices in chapter 3, occasional swings (jumps) in the price can be observed for both directions upwards and downwards, followed by reversals towards a central tendency (mean reversion). These swings can be mostly attributed to short-term disturbances to either the supply or demand side, or both. Moreover, it has also been established that energy commodity prices tend to exhibit positive skewness mostly because of the fact that when supplies are ample, two factors can influence and equilibrate the supply and demand relationship: the price of the commodity and its level of inventories. Thus theoretically, by increasing inventories and decreasing the price, the desirable supply-demand equilibrium can be achieved. However, when inventories are scarce and new supplies of the physical commodity cannot be found in the short-run, it is only the price that can be adjusted upwards to equilibrate supply and demand. The continuous monitoring of risk, with the use of the most efficient VaR techniques for decision support on a daily basis, is a necessity for all energy market players.

4.5. Empirical analysis

To evaluate the efficiency of all available VaR models, out-of-sample 99%[24] one-day VaR forecasts are generated for each one of the energy commodities examined and the SEI. The period used to estimate the parametric VaR models is the 12/09/2000 to 12/09/2007 consisting of 1827 observations, whereas the period used for the 623 out-of-sample forecasts is the 13/09/2007 to 1/02/2010. This research contributes to the relevant literature by testing

[24] 95% one-day VaR forecasts are also calculated but are not reported because results are very similar with the 99% forecasts that are reported in the tables.

all the VaR models for both long and short trading positions undertaken by the energy market players. As Angelidis and Degiannakis (2005) argue, it is imperative that a risk manager is able to forecast accurately the VaR for both long and short trading positions. In total, twenty two VaR models are implemented on the energy spot price series and the Spot Energy index, as described previously.

The VaR results for all applied models and for all energy commodities and the SEI are shown in tables 4-2 to 4-10, for the 1% significance level. Each table reports, for both long and short positions, the average VaR or Expected Tail Loss in percentage points, the frequency of violations or number of hits in percentage points, alongside the p-values for Christoffersen's three statistical tests for unconditional coverage, independence, and conditional coverage. The models that pass each test at the 5% significance level, and thus do not reject the null hypothesis, are indicated in bold. A 5% significance level is chosen in this thesis as the acceptance threshold for the three tests, because the smaller the significance level the fewer the number of violations is, which leads to larger Type II errors that can be very costly for the risk manager. In addition, the results from the second evaluation stage, i.e. the Expected Shortfall, and the Loss Function that measures the economic accuracy of the models, are reported for both the short and long positions. The model that minimizes the total loss, hence returns the lowest LF value, is preferred relative to the remaining models. The numbers indicated in bold represent the models that have successfully passed all three statistical tests, whereas an asterisk indicates in each case the model that provides the smallest LF value and that is later used in the MDM pair-wise comparison as the benchmark model. The economic evaluation framework that uses the proposed LF can provide useful information for evaluating the VaR estimates for regulatory purposes. That is because by using the ES measure in the LF, the additional information on the magnitude of a loss that exceeds the estimated VaR is incorporated into the evaluation process. In addition, with the use of the proposed LF, the risk manager is able to rank all the candidate VaR models and distinguish the best performing one amongst them.

From tables 4-2 to 4-10 it can be seen that for all commodities and the SEI there is always at least one model that passes all three statistical tests at the 1% significance level, for both long and short trading positions. In the majority of cases, it is the MC simulation and the proposed Hybrid MC-HS models that successfully pass the first evaluation stage, thus overall prevailing against the more traditional ARCH type and Historical Simulation methodologies.

Even though in some cases the MC simulation models do not pass all three statistical tests, they tend to produce the lowest LF values, followed by the Hybrid MC-HS models. Due to the economic importance of the LF for the risk manager, it can be argued that even for those energy commodities that the simulation-type models do not pass the statistical tests, they can still be considered as good alternative methodologies for estimating VaR. When the frequency of hits is zero the respective models are unsuitable candidates for the application of both the statistical and the economic evaluation tests; these cases are indicated by a dash line in all tables. In addition, in those cases where the frequency of hits is too high, above 20%, the respective models are unsuitable candidates for the application of the two statistical tests for unconditional and conditional coverage; in these cases a dash is also inserted. However, this does not mean that these models should be immediately rejected but it should be noted that consistently overestimate in the former case, and underestimate in the latter case, the actual VaR. For the entire fuels complex, including the WTI, HO, Gasoline, and the crack spreads with WTI, and for both long and short positions, the MC simulations methodology under the MRJD specifications, is the one that manages to pass all three statistical criteria from the first evaluation stage, and at the same time to deliver the lowest LF at the second evaluation stage. The only exceptions are the WTI and the CS-HO-WTI just for the long trading positions, with the F-EGARCH and F-GARCH methodologies delivering the lowest LFs respectively. As for the PJM and the SEI, and for both the long and the short trading positions, it is the Hybrid MC-HS specifications that successfully pass the first evaluation stage and deliver the lowest LF values at the second evaluation stage. Finally, the VaR for both the NG and the Propane series, for the long positions, is best estimated by the F-EGARCH methodology, whereas for the short positions is best estimated with the Hybrid MC-HS and the GARCH methodologies respectively.

Table 4-2: VaR results for WTI at a=1%.

VaR results for all applied models and for all energy commodities and the SEI, for the 1% significance level, and for both long and short positions. The table reports the average VaR or Expected Tail Loss (ETL) in percentage points, the frequency of violations or number of hits in percentage points, alongside the p-values for Christoffersen's three statistical tests for unconditional coverage, independence, and conditional coverage (as explained in more detail in chapter 4.2). The models that pass each test at the 5% significance level, and thus they do not reject the null hypothesis, are indicated in bold. In addition, the results from the second evaluation stage, i.e. the Expected Shortfall, and the Loss Function that measures the economic accuracy of the models, are reported for both the short and long positions. The model that minimizes the total loss, hence returns the lowest LF value, is preferred relative to the remaining models. The numbers indicated in bold represent the models that have successfully passed all three statistical tests, whereas an asterisk indicates in each case the model that provides the smallest LF value and that is later used in the MDM pair-wise comparison as the benchmark model. In those cases where the frequency of hits is zero the respective models are unsuitable candidates for the application of both the statistical and the economic evaluation tests; in these cases a dash is inserted. In addition, in those cases where the frequency of hits is too high, above 20%, the respective models are unsuitable candidates for the application of the two statistical tests for unconditional and conditional coverage; in these cases a dash is also inserted.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	2.30%	2.31%	31.46%	32.58%	-	-	**26.40%**	0.03%	-	-	-3.30%	3.28%	1.373	1.963
	HS	2.03%	3.58%	4.17%	3.69%	0.00%	0.00%	**10.30%**	**25.05%**	0.00%	0.00%	-8.33%	9.57%	0.090	0.305
	F-HS	1.95%	3.51%	3.69%	3.37%	0.00%	0.00%	**25.05%**	**66.88%**	0.00%	0.00%	-8.44%	9.86%	0.083	0.282
	V&C	2.44%	3.76%	4.98%	3.85%	0.00%	0.00%	1.60%	**6.62%**	0.00%	0.00%	-7.98%	9.43%	0.115	0.317
	GARCH	1.43%	2.45%	0.96%	1.77%	**92.58%**	**8.30%**	**71.20%**	51.11%	**70.34%**	**6.38%**	-8.05%	9.48%	**0.110**	**0.312**
	F-GARCH	1.24%	2.70%	1.12%	1.44%	**76.11%**	**29.56%**	**66.97%**	**58.80%**	**60.04%**	**23.89%**	-8.34%	10.40%	**0.089**	**0.244**
	EGARCH	2.34%	2.52%	1.93%	2.41%	3.93%	0.28%	**47.47%**	**37.40%**	2.92%	0.18%	-9.35%	10.03%	0.039	0.269
	F-EGARCH	2.38%	2.38%	1.77%	2.25%	**8.30%**	0.72%	**51.11%**	**40.61%**	**6.38%**	0.49%	-9.50%	10.42%	**0.034***	0.242
	GBM	2.45%	2.51%	47.83%	45.26%	-	-	**10.34%**	**20.44%**	-	-	-2.49%	2.60%	1.958	2.438
HYBRID MC-HS	MR-OLS	2.10%	3.59%	4.0%	3.7%	0.00%	0.00%	**8.31%**	**25.05%**	0.00%	0.00%	-8.45%	9.57%	0.082	0.305
	MR-GARCH	2.09%	3.74%	4.01%	3.53%	0.00%	0.00%	**8.31%**	**71.36%**	0.00%	0.00%	-8.45%	9.73%	0.082	0.292
	MR-EGARCH	2.09%	3.59%	4.0%	3.7%	0.00%	0.00%	**8.31%**	**25.05%**	0.00%	0.00%	-8.45%	9.57%	0.082	0.305
	MRJD-OLS	2.37%	3.92%	5.14%	3.85%	0.00%	0.00%	0.40%	**6.62%**	0.00%	0.00%	-7.91%	9.43%	0.121	0.317
	MRJD-GARCH	2.31%	3.91%	5.30%	3.85%	0.00%	0.00%	0.57%	**6.62%**	0.00%	0.00%	-7.84%	9.43%	0.127	0.317
	MRJD-EGARCH	2.53%	3.94%	4.82%	3.85%	0.00%	0.00%	1.18%	**6.62%**	0.00%	0.00%	-8.08%	9.43%	0.107	0.317
MC SIMULATIONS	GBM	2.62%	3.64%	5.14%	4.33%	0.00%	0.00%	2.14%	**12.59%**	0.00%	0.00%	-7.92%	9.00%	0.120	0.357
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	2.78%	2.50%	1.61%	1.77%	**16.29%**	**8.30%**	**54.90%**	**51.11%**	**12.88%**	**6.38%**	-5.90%	9.06%	**0.402**	**0.351**
	MRJD-GARCH	2.27%	2.32%	1.12%	1.12%	**76.11%**	**76.11%**	**66.97%**	**66.97%**	**60.04%**	**60.04%**	-6.44%	10.94%	**0.299**	**0.209***
	MRJD-EGARCH	2.45%	2.50%	1.44%	1.44%	**29.56%**	**29.56%**	**58.80%**	**58.80%**	**23.89%**	**23.89%**	-6.37%	10.77%	**0.311**	**0.220**

Table 4-3: VaR results for HO at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	2.04%	1.93%	32.10%	32.10%	-	-	**10.68%**	0.30%	-	-	-2.82%	2.74%	1.059	1.146
	HS	2.10%	2.44%	2.57%	1.61%	0.10%	**16.29%**	**34.36%**	**54.90%**	0.06%	**12.88%**	-8.30%	9.35%	0.041	**0.114**
	F-HS	2.02%	2.88%	2.57%	1.28%	0.10%	**49.48%**	**34.36%**	**62.83%**	0.06%	**40.26%**	-8.30%	9.90%	0.041	**0.096**
	V&C	2.11%	2.68%	2.89%	2.09%	0.01%	1.74%	**28.74%**	**43.96%**	0.01%	1.24%	-8.10%	8.77%	0.048	0.136
	GARCH	1.62%	3.34%	1.77%	0.96%	**8.30%**	**92.58%**	**51.11%**	**71.20%**	**6.38%**	**70.34%**	-8.60%	9.74%	**0.031**	**0.101**
	F-GARCH	1.56%	2.79%	1.93%	0.96%	3.93%	**92.58%**	**47.47%**	**71.20%**	2.92%	**70.34%**	-8.31%	9.74%	0.040	**0.101**
	EGARCH	1.44%	2.23%	2.09%	1.44%	1.74%	**29.56%**	**43.96%**	**58.80%**	1.24%	**23.89%**	-8.20%	8.82%	0.045	**0.134**
	F-EGARCH	1.61%	3.30%	1.93%	0.80%	3.93%	**60.80%**	**47.47%**	**75.53%**	2.92%	**54.84%**	-8.41%	10.30%	0.037	**0.086**
HYBRID MC-HS	GBM	2.19%	2.14%	46.39%	45.59%	-	-	**18.92%**	**18.31%**	-	-	-2.22%	2.23%	1.418	1.451
	MR-OLS	1.96%	2.74%	2.7%	1.4%	0.04%	**29.56%**	**31.47%**	**58.80%**	0.02%	**23.89%**	-8.21%	9.59%	0.044	0.106
	MR-GARCH	2.09%	2.73%	2.57%	1.44%	0.10%	**29.56%**	**34.36%**	**58.80%**	0.06%	**23.89%**	-8.30%	9.59%	0.041	0.106
	MR-EGARCH	1.97%	2.74%	2.7%	1.4%	0.04%	**29.56%**	**31.47%**	**58.80%**	0.02%	**23.89%**	-8.21%	9.59%	0.044	0.106
	MRJD-OLS	2.54%	2.85%	2.89%	2.41%	0.01%	0.28%	**28.74%**	**37.40%**	0.01%	0.18%	-8.10%	8.40%	0.048	0.152
	MRJD-GARCH	2.56%	2.84%	2.89%	2.41%	0.01%	0.28%	**28.74%**	**37.40%**	0.01%	0.18%	-8.10%	8.40%	0.048	0.152
	MRJD-EGARCH	2.56%	2.86%	2.89%	2.41%	0.01%	0.28%	**28.74%**	**37.40%**	0.01%	0.18%	-8.10%	8.40%	0.048	0.152
MC SIMULATIONS	GBM	2.14%	2.52%	2.89%	2.25%	0.01%	0.72%	**28.74%**	**40.61%**	0.01%	0.49%	-8.10%	8.58%	0.048	0.144
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	2.36%	2.54%	1.12%	0.64%	**76.11%**	**33.66%**	**66.97%**	**79.93%**	**60.04%**	**32.02%**	-8.06%	10.40%	**0.050**	**0.083***
	MRJD-GARCH	1.93%	7.78%	0.80%	0.16%	**60.80%**	0.89%	**75.53%**	**93.61%**	**54.84%**	0.89%	-8.61%	17.58%	**0.031***	0.000
	MRJD-EGARCH	1.81%	4.19%	1.12%	0.32%	**76.11%**	4.70%	**66.97%**	**88.94%**	**60.04%**	4.65%	-8.06%	11.69%	**0.050**	0.056

Table 4-4: VaR results for GASOLINE at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	2.45%	2.38%	30.50%	32.26%	-	-	**1.40%**	0.07%	-	-	-3.47%	3.36%	**1.808**	2.020
	HS	2.37%	4.78%	1.93%	1.93%	3.93%	3.93%	**47.47%**	**47.47%**	2.92%	2.92%	-11.00%	12.40%	0.136	0.054
	F-HS	2.20%	4.33%	1.93%	1.93%	3.93%	3.93%	**47.47%**	**47.47%**	2.92%	2.92%	-10.96%	12.40%	0.138	0.054
	V&C	2.47%	5.12%	3.53%	1.93%	0.00%	3.93%	**21.31%**	**47.47%**	0.00%	2.92%	-9.63%	12.40%	0.207	0.054
	GARCH	2.96%	3.39%	1.77%	2.09%	**8.30%**	1.74%	0.35%	**43.96%**	2.80%	1.24%	-10.40%	11.81%	0.163	0.077
	F-GARCH	2.63%	3.00%	1.12%	1.93%	**76.11%**	3.93%	**66.97%**	**47.47%**	**60.04%**	2.92%	-11.36%	12.25%	0.123	0.059
	EGARCH	2.86%	3.49%	1.93%	2.09%	3.93%	1.74%	**21.58%**	**43.96%**	1.62%	1.24%	-10.41%	11.81%	0.163	0.077
	F-EGARCH	2.34%	3.15%	1.28%	1.93%	**49.48%**	3.93%	**62.83%**	**47.47%**	**40.26%**	2.92%	-10.90%	12.25%	0.140	0.059
	GBM	2.69%	2.56%	44.62%	45.43%	-	-	**15.19%**	**20.87%**	-	-	-2.73%	2.67%	2.367	2.522
HYBRID MC-HS	MR-OLS	2.58%	4.82%	1.8%	1.9%	**8.30%**	3.93%	**51.11%**	**47.47%**	**6.38%**	2.92%	-11.23%	12.40%	**0.128**	0.054
	MR-GARCH	2.59%	4.82%	1.77%	1.93%	**8.30%**	3.93%	**51.11%**	**47.47%**	**6.38%**	2.92%	-11.23%	12.40%	**0.128**	0.054
	MR-EGARCH	2.58%	4.82%	1.8%	1.9%	**8.30%**	3.93%	**51.11%**	**47.47%**	**6.38%**	2.92%	-11.23%	12.40%	**0.128**	0.054
	MRJD-OLS	2.82%	4.00%	3.69%	2.73%	0.00%	0.04%	**25.05%**	**45.70%**	0.00%	0.03%	-9.51%	10.82%	0.216	0.132
	MRJD-GARCH	2.80%	4.00%	3.69%	2.73%	0.00%	0.04%	**25.05%**	**45.70%**	0.00%	0.03%	-9.51%	10.82%	0.216	0.132
	MRJD-EGARCH	2.80%	4.24%	3.69%	2.57%	0.00%	0.10%	**25.05%**	**34.36%**	0.00%	0.06%	-9.51%	11.07%	0.216	0.115
MC SIMULATIONS	GBM	2.64%	4.30%	3.53%	2.41%	0.00%	0.28%	**21.31%**	**37.40%**	0.00%	0.18%	-9.63%	11.35%	0.207	0.099
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	3.80%	3.45%	0.96%	0.96%	**92.58%**	**92.58%**	**71.20%**	**71.20%**	**70.34%**	**70.34%**	-10.33%	10.90%	**0.167**	**0.126**
	MRJD-GARCH	3.97%	3.43%	0.80%	0.80%	**60.80%**	**60.80%**	**75.53%**	**75.53%**	**54.84%**	**54.84%**	-12.64%	12.19%	**0.088**	**0.061**
	MRJD-EGARCH	4.06%	3.96%	0.80%	0.80%	**60.80%**	**60.80%**	**75.53%**	**75.53%**	**54.84%**	**54.84%**	-12.64%	12.19%	**0.088***	**0.061***

Table 4-5: VaR results for CS_GASOLINE_WTI at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	1.27%	1.24%	31.30%	33.71%	-	-	**7.92%**	0.48%	-	-	-1.80%	1.73%	1.000	1.101
	HS	2.41%	2.86%	2.73%	2.41%	0.04%	0.28%	**45.70%**	**37.40%**	0.03%	0.18%	-6.72%	7.37%	0.146	0.146
	F-HS	2.25%	2.66%	2.25%	1.93%	0.72%	3.93%	**30.42%**	**47.47%**	0.40%	2.92%	-6.95%	7.95%	0.134	0.122
	V&C	2.19%	2.44%	4.33%	4.01%	0.00%	0.00%	**42.91%**	**14.01%**	0.00%	0.00%	-5.77%	6.02%	0.207	0.230
	GARCH	1.82%	2.30%	2.41%	2.41%	0.28%	0.28%	**37.40%**	**35.29%**	0.18%	0.17%	-5.32%	6.16%	0.243	0.220
	F-GARCH	2.63%	2.04%	1.12%	1.61%	**76.11%**	**16.29%**	**66.97%**	**54.90%**	**60.04%**	**12.88%**	-6.55%	6.94%	**0.155**	**0.168**
	EGARCH	1.69%	2.34%	3.21%	2.89%	0.00%	0.01%	**23.77%**	**51.11%**	0.00%	0.01%	-5.60%	5.93%	0.220	0.238
	F-EGARCH	2.44%	2.05%	1.28%	1.93%	**49.48%**	3.93%	**62.83%**	**47.47%**	**40.26%**	2.92%	-6.61%	6.97%	**0.152**	0.166
HYBRID MC-HS	GBM	1.37%	1.39%	46.23%	46.07%	-	-	**15.00%**	**19.04%**	-	-	-1.40%	1.42%	1.192	1.248
	MR-OLS	2.40%	2.87%	2.7%	2.4%	0.04%	0.28%	**45.70%**	**37.40%**	0.03%	0.18%	-6.72%	7.37%	0.146	0.146
	MR-GARCH	2.07%	2.90%	2.73%	2.25%	0.04%	0.72%	**45.70%**	**40.61%**	0.03%	0.49%	-6.72%	7.60%	0.146	0.136
	MR-EGARCH	2.42%	2.87%	2.7%	2.4%	0.04%	0.28%	**45.70%**	**37.40%**	0.03%	0.18%	-6.72%	7.37%	0.146	0.146
	MRJD-OLS	2.02%	2.52%	6.90%	5.14%	0.00%	0.00%	**70.49%**	1.24%	0.00%	0.00%	-4.75%	5.39%	0.301	0.287
	MRJD-GARCH	2.01%	2.61%	6.90%	4.98%	0.00%	0.00%	**70.49%**	0.24%	0.00%	0.00%	-4.75%	5.47%	0.301	0.279
	MRJD-EGARCH	2.01%	2.46%	6.90%	5.30%	0.00%	0.00%	**70.49%**	1.23%	0.00%	0.00%	-4.75%	5.31%	0.301	0.294
MC SIMULATIONS	GBM	2.38%	2.59%	4.98%	4.65%	0.00%	0.00%	**24.99%**	-	0.00%	-	-5.45%	5.65%	0.232	0.262
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	2.73%	4.86%	2.25%	0.48%	0.72%	**14.80%**	**40.61%**	**84.40%**	0.49%	**14.43%**	-5.97%	11.25%	0.192	**0.044**
	MRJD-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-EGARCH	2.93%	4.14%	0.80%	0.48%	**60.80%**	**14.80%**	75.53%	**84.40%**	**54.84%**	**14.43%**	-9.83%	11.25%	**0.033***	**0.044***

Table 4-6: VaR results for CS_HO_WTI at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	0.87%	0.86%	31.46%	31.46%	-	-	1.07%	**7.19%**	-	-	-1.25%	1.20%	0.420	0.408
	HS	1.80%	1.71%	2.73%	2.09%	0.04%	1.74%	**31.47%**	**43.96%**	0.02%	1.24%	-4.56%	4.83%	0.064	0.055
	F-HS	1.97%	1.34%	1.93%	1.93%	3.93%	3.93%	**47.47%**	**47.47%**	2.92%	2.92%	-5.06%	4.90%	0.046	0.053
	V&C	1.60%	1.38%	4.01%	4.49%	0.00%	0.00%	**77.46%**	**69.36%**	0.00%	0.00%	-3.85%	3.58%	0.098	0.104
	GARCH	1.55%	1.40%	2.57%	2.57%	0.10%	0.10%	**40.40%**	**34.36%**	0.07%	0.06%	-4.30%	3.96%	0.076	0.086
	F-GARCH	1.85%	1.41%	1.28%	1.12%	**49.48%**	**76.11%**	**62.83%**	**66.97%**	**40.26%**	**60.04%**	-5.55%	4.85%	**0.033***	**0.054**
	EGARCH	1.69%	1.64%	2.73%	2.57%	0.04%	0.10%	**45.70%**	**34.36%**	0.03%	0.06%	-4.26%	4.05%	0.077	0.082
	F-EGARCH	2.24%	1.90%	1.28%	1.12%	**49.48%**	**76.11%**	**62.83%**	**66.97%**	**40.26%**	**60.04%**	-5.55%	5.54%	**0.033**	**0.038**
HYBRID MC-HS	GBM	0.95%	0.89%	45.75%	47.83%	-	-	**21.17%**	4.15%	-	-	-0.97%	0.92%	0.503	0.494
	MR-OLS	1.80%	1.72%	2.7%	2.1%	0.04%	1.74%	**31.47%**	**43.96%**	0.02%	1.24%	-4.56%	4.83%	0.064	0.055
	MR-GARCH	1.82%	1.76%	2.73%	2.09%	0.04%	1.74%	**31.47%**	**43.96%**	0.02%	1.24%	-4.56%	4.83%	0.064	0.055
	MR-EGARCH	1.79%	1.72%	2.7%	2.1%	0.04%	1.74%	**31.47%**	**43.96%**	0.02%	1.24%	-4.56%	4.83%	0.064	0.055
	MRJD-OLS	1.56%	1.42%	5.30%	5.46%	0.00%	0.00%	**70.15%**	**42.49%**	0.00%	0.00%	-3.44%	3.33%	0.123	0.120
	MRJD-GARCH	1.53%	1.41%	5.46%	5.46%	0.00%	0.00%	**72.46%**	**42.49%**	0.00%	0.00%	-3.39%	3.33%	0.127	0.120
	MRJD-EGARCH	1.56%	1.42%	5.30%	5.46%	0.00%	0.00%	**70.15%**	**42.49%**	0.00%	0.00%	-3.44%	3.33%	0.123	0.120
MC SIMULATIONS	GBM	1.57%	1.50%	5.14%	5.14%	0.00%	0.00%	**66.70%**	**51.24%**	0.00%	0.00%	-3.49%	3.41%	0.120	0.114
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	2.22%	2.36%	2.57%	1.77%	0.10%	**8.30%**	**34.36%**	**51.11%**	0.06%	**6.38%**	-4.36%	5.10%	0.073	**0.048**
	MRJD-GARCH	1.67%	1.44%	0.32%	0.48%	4.70%	**14.80%**	**88.94%**	**84.40%**	4.65%	**14.43%**	-7.64%	7.27%	0.004	**0.013***
	MRJD-EGARCH	2.41%	2.14%	1.44%	1.44%	**29.56%**	**29.56%**	**58.80%**	**58.80%**	**23.89%**	**23.89%**	-5.50%	5.23%	**0.034**	**0.044**

Table 4-7: VaR results for NG at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	2.84%	2.65%	32.91%	31.62%	-	-	3.33%	**11.34%**	-	-	-3.97%	3.94%	2.327	3.574
	HS	4.17%	5.04%	0.80%	1.44%	**60.80%**	**29.56%**	2.65%	**11.07%**	2.28%	**5.65%**	-15.88%	17.08%	0.108	**0.169**
	F-HS	3.69%	3.81%	0.96%	1.93%	**92.58%**	3.93%	4.16%	**21.58%**	4.14%	1.62%	-15.00%	15.58%	0.133	0.260
	V&C	3.25%	5.76%	1.28%	1.61%	**49.48%**	**16.29%**	0.00%	**14.18%**	0.00%	4.27%	-14.10%	16.66%	0.163	0.191
	GARCH	2.33%	3.73%	1.93%	1.28%	3.93%	**49.48%**	**21.58%**	**62.83%**	1.62%	**40.26%**	-12.00%	13.64%	0.263	**0.431**
	F-GARCH	3.08%	4.23%	1.12%	0.96%	**76.11%**	**92.58%**	**66.97%**	**71.20%**	**60.04%**	**70.34%**	-12.47%	15.04%	**0.236**	**0.301**
	EGARCH	2.51%	3.78%	1.77%	1.77%	**8.30%**	**8.30%**	**17.69%**	**17.69%**	2.80%	2.80%	-12.35%	14.66%	0.242	0.334
	F-EGARCH	3.13%	3.87%	1.12%	1.28%	**76.11%**	**49.48%**	**66.97%**	**62.83%**	**60.04%**	**40.26%**	-12.65%	13.64%	**0.227***	**0.431**
HYBRID MC-HS	GBM	3.07%	3.00%	45.59%	45.75%	-	-	**19.13%**	3.70%	-	-	-3.18%	3.12%	2.973	4.319
	MR-OLS	4.09%	5.11%	0.8%	1.4%	**60.80%**	**29.56%**	2.65%	**11.07%**	2.28%	**5.65%**	-15.88%	17.08%	0.108	**0.169**
	MR-GARCH	4.11%	5.09%	0.80%	1.44%	**60.80%**	**29.56%**	2.65%	**11.07%**	2.28%	**5.65%**	-15.88%	17.08%	0.108	**0.169**
	MR-EGARCH	4.08%	5.10%	0.8%	1.4%	**60.80%**	**29.56%**	2.65%	**11.07%**	2.28%	**5.65%**	-15.88%	17.08%	0.108	**0.169***
	MRJD-OLS	2.79%	5.73%	2.41%	2.09%	0.28%	1.74%	0.36%	**25.84%**	0.00%	0.84%	-12.21%	15.17%	0.251	0.291
	MRJD-GARCH	2.81%	5.70%	2.41%	2.09%	0.28%	1.74%	0.36%	**25.84%**	0.00%	0.84%	-12.21%	15.17%	0.251	0.291
	MRJD-EGARCH	2.84%	5.75%	2.41%	2.09%	0.28%	1.74%	0.36%	**25.84%**	0.00%	0.84%	-12.21%	15.17%	0.251	0.291
MC SIMULATIONS	GBM	4.49%	5.30%	0.80%	1.61%	**60.80%**	**16.29%**	2.65%	**14.18%**	2.28%	4.27%	-15.88%	16.66%	0.108	0.191
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	3.11%	-	0.32%	0.00%	4.70%	-	**88.94%**	-	4.65%	-	-18.51%	-	0.050	-
	MRJD-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-

Table 4-8: VaR results for PROPANE at a=1%.

For further details, see notes in Table 3.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	1.87%	1.51%	29.53%	34.83%	-	-	**26.40%**	0.03%	-	-	-1.54%	1.25%	2.590	1.742
	HS	4.13%	3.05%	1.77%	1.77%	0.00%	0.00%	**10.30%**	**25.05%**	0.00%	0.00%	-4.59%	1.53%	1.114	1.529
	F-HS	4.27%	2.72%	1.61%	1.77%	0.00%	0.00%	**25.05%**	**66.88%**	0.00%	0.00%	-4.88%	1.49%	1.043	1.559
	V&C	3.78%	3.36%	2.57%	1.77%	0.00%	0.00%	1.60%	6.62%	0.00%	0.00%	-4.25%	1.46%	1.210	1.575
	GARCH	2.42%	2.36%	2.57%	2.25%	**92.58%**	**8.30%**	**71.20%**	**51.11%**	**70.34%**	**6.38%**	-4.27%	1.84%	**1.204**	**1.327***
	F-GARCH	2.54%	2.78%	1.77%	1.61%	**76.11%**	**29.56%**	**66.97%**	**58.80%**	**60.04%**	**23.89%**	-3.98%	1.53%	**1.293**	**1.526**
	EGARCH	2.65%	2.75%	3.21%	2.09%	3.93%	0.28%	**47.47%**	**37.40%**	2.92%	0.18%	-4.20%	1.82%	1.223	1.343
	F-EGARCH	2.98%	2.53%	1.93%	1.93%	**8.30%**	0.72%	**51.11%**	**40.61%**	**6.38%**	0.49%	-4.43%	1.73%	**1.157***	1.396
HYBRID MC-HS	GBM	2.00%	1.74%	42.22%	47.19%	-	-	**10.34%**	**20.44%**	-	-	-1.08%	1.11%	3.015	1.858
	MR-OLS	4.13%	3.06%	1.8%	1.8%	0.00%	0.00%	**8.31%**	**25.05%**	0.00%	0.00%	-4.77%	1.53%	1.069	1.529
	MR-GARCH	4.13%	3.06%	1.77%	1.77%	0.00%	0.00%	**8.31%**	**71.36%**	0.00%	0.00%	-4.77%	1.73%	1.069	1.392
	MR-EGARCH	4.11%	3.08%	1.8%	1.8%	0.00%	0.00%	**8.31%**	**25.05%**	0.00%	0.00%	-4.77%	1.53%	1.069	1.529
	MRJD-OLS	2.94%	2.55%	4.33%	3.37%	0.00%	0.00%	0.40%	**6.62%**	0.00%	0.00%	-4.35%	1.46%	1.180	1.575
	MRJD-GARCH	2.86%	2.54%	4.49%	3.37%	0.00%	0.00%	0.57%	**6.62%**	0.00%	0.00%	-4.32%	1.46%	1.189	1.575
	MRJD-EGARCH	2.86%	2.55%	4.49%	3.37%	0.00%	0.00%	1.18%	**6.62%**	0.00%	0.00%	-4.41%	1.46%	1.164	1.575
MC SIMULATIONS	GBM	3.91%	3.14%	2.57%	1.93%	0.00%	0.00%	2.14%	**12.59%**	0.00%	0.00%	-4.27%	1.69%	1.204	1.423
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	3.72%	5.10%	1.28%	0.48%	**16.29%**	**8.30%**	**54.90%**	**51.11%**	**12.88%**	**6.38%**	-2.01%	1.03%	**2.239**	**1.930**
	MRJD-GARCH	3.74%	4.46%	0.48%	0.32%	**76.11%**	**76.11%**	**66.97%**	**66.97%**	**60.04%**	**60.04%**	-2.13%	- 0.52%	**2.157**	**4.335**
	MRJD-EGARCH	4.94%	5.15%	0.64%	0.32%	**29.56%**	**29.56%**	**58.80%**	**58.80%**	**23.89%**	**23.89%**	-2.43%	1.08%	1.971	**1.890**

Table 4-9: VaR results for PJM at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	10.44%	11.49%	25.84%	25.68%	-	-	**7.15%**	**42.91%**	-	-	-13.80%	14.34%	30.366	33.349
	HS	13.42%	12.94%	0.80%	1.12%	**60.80%**	**76.11%**	**75.53%**	**66.97%**	**54.84%**	**60.04%**	-58.75%	55.58%	**0.739**	**0.360**
	F-HS	10.84%	11.01%	0.96%	1.28%	**92.58%**	**49.48%**	**71.20%**	**62.83%**	**70.34%**	**40.26%**	-56.50%	53.84%	**0.932**	**0.522**
	V&C	14.28%	11.81%	1.61%	2.57%	**16.29%**	0.10%	**54.90%**	**40.40%**	**12.88%**	0.07%	-49.38%	46.42%	**1.858**	**1.759**
	GARCH	12.00%	12.98%	1.28%	2.57%	**49.48%**	0.10%	**62.83%**	**40.40%**	**40.26%**	0.07%	-44.68%	40.92%	**2.767**	3.269
	F-GARCH	8.81%	12.44%	0.80%	1.61%	**60.80%**	**16.29%**	**75.53%**	**14.18%**	**54.84%**	4.27%	-45.96%	45.05%	**2.490**	**2.085**
	EGARCH	13.05%	12.74%	1.77%	2.89%	**8.30%**	0.01%	**51.11%**	**51.11%**	**6.38%**	0.01%	-40.24%	41.38%	**3.969**	**3.118**
	F-EGARCH	11.22%	13.81%	1.12%	1.61%	**76.11%**	**16.29%**	**66.97%**	**54.90%**	**60.04%**	**12.88%**	-36.71%	45.36%	**5.250**	2.007
HYBRID MC-HS	GBM	10.16%	11.04%	39.97%	36.92%	-	-	2.15%	0.62%	-	-	-10.47%	11.40%	39.520	41.837
	MR-OLS	13.43%	12.93%	0.8%	1.1%	**60.80%**	76.11%	**75.53%**	**66.97%**	**54.84%**	**60.04%**	-58.75%	55.58%	**0.739**	**0.360**
	MR-GARCH	16.70%	13.01%	0.64%	1.12%	**33.66%**	**76.11%**	**79.93%**	**66.97%**	**32.02%**	**60.04%**	-62.06%	55.58%	**0.521***	**0.360**
	MR-EGARCH	13.44%	12.82%	0.8%	1.1%	**60.80%**	**76.11%**	**75.53%**	**66.97%**	**54.84%**	**60.04%**	-58.75%	55.58%	**0.739**	**0.360***
	MRJD-OLS	15.60%	12.24%	1.61%	2.73%	**16.29%**	0.04%	**54.90%**	**45.70%**	**12.88%**	0.03%	-49.38%	45.67%	**1.858**	**1.933**
	MRJD-GARCH	15.80%	12.37%	1.61%	2.73%	**16.29%**	0.04%	**54.90%**	**45.70%**	**12.88%**	0.03%	-49.38%	45.67%	**1.858**	**1.933**
	MRJD-EGARCH	15.65%	12.15%	1.61%	2.73%	**16.29%**	0.04%	**54.90%**	**45.70%**	**12.88%**	0.03%	-49.38%	45.67%	**1.858**	**1.933**
MC SIMULATIONS	GBM	14.19%	11.09%	1.61%	2.57%	**16.29%**	0.10%	**54.90%**	**40.40%**	**12.88%**	0.07%	-49.38%	46.42%	**1.858**	1.759
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-

Table 4-10: VaR results for SEI at a=1%.

For further details, see notes in previous table.

		Avg VaR (ETL)		No Hits (%)		LR_{uc}		LR_{ind}		LR_{cc}		ES		LF (x10^4)	
		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
	RM	2.10%	2.00%	31.94%	32.58%	-	-	3.01%	**35.89%**	-	-	-2.86%	2.78%	0.970	1.115
	HS	1.42%	1.05%	1.12%	1.12%	**76.11%**	**76.11%**	**66.97%**	**66.97%**	**60.04%**	**60.04%**	-9.00%	9.39%	**0.030**	**0.002**
	F-HS	1.19%	1.12%	1.44%	1.12%	**29.56%**	**76.11%**	**58.80%**	**66.97%**	**23.89%**	**60.04%**	-8.68%	9.39%	**0.035**	**0.002**
	V&C	1.13%	1.55%	2.09%	2.41%	1.74%	0.28%	**43.96%**	**37.40%**	1.24%	0.18%	-8.19%	8.54%	0.044	0.013
	GARCH	2.00%	1.78%	1.12%	2.09%	**76.11%**	1.74%	**66.97%**	**43.96%**	**60.04%**	1.24%	-8.63%	8.35%	**0.036**	0.017
	F-GARCH	1.94%	1.73%	0.96%	1.28%	**92.58%**	**49.48%**	**71.20%**	**62.83%**	**70.34%**	**40.26%**	-8.76%	8.82%	**0.034**	**0.008**
	EGARCH	2.03%	1.82%	1.28%	2.25%	**49.48%**	0.72%	**62.83%**	**40.61%**	**40.26%**	0.49%	-8.63%	8.36%	**0.036**	0.017
	F-EGARCH	1.94%	1.60%	1.12%	1.44%	**76.11%**	**29.56%**	**66.97%**	**58.80%**	**60.04%**	**23.89%**	-8.63%	9.00%	**0.036**	**0.006**
HYBRID MC-HS	GBM	2.18%	2.07%	47.51%	48.64%	-	-	**6.33%**	**9.18%**	-	-	-2.23%	2.16%	1.360	1.510
	MR-OLS	1.26%	1.11%	1.3%	1.1%	**49.48%**	**76.11%**	**62.83%**	**66.97%**	**40.26%**	**60.04%**	-8.83%	9.39%	**0.033**	**0.002**
	MR-GARCH	1.43%	1.13%	1.12%	1.12%	**76.11%**	**76.11%**	**66.97%**	**66.97%**	**60.04%**	**60.04%**	-9.00%	9.39%	**0.030**	**0.002**
	MR-EGARCH	1.40%	1.15%	1.1%	1.1%	**76.11%**	**76.11%**	**66.97%**	**66.97%**	**60.04%**	**60.04%**	-9.00%	9.39%	**0.030***	**0.002***
	MRJD-OLS	1.32%	1.38%	1.77%	2.09%	**8.30%**	1.74%	**51.11%**	**43.96%**	**6.38%**	1.24%	-8.40%	8.76%	**0.040**	0.009
	MRJD-GARCH	1.32%	1.37%	1.77%	2.09%	**8.30%**	1.74%	**51.11%**	**43.96%**	**6.38%**	1.24%	-8.40%	8.76%	**0.040**	0.009
	MRJD-EGARCH	1.30%	1.37%	1.77%	2.09%	**8.30%**	1.74%	**51.11%**	**43.96%**	**6.38%**	1.24%	-8.40%	8.76%	**0.040**	0.009
MC SIMULATIONS	GBM	1.25%	1.43%	1.77%	2.25%	**8.30%**	0.72%	**51.11%**	**40.61%**	**6.38%**	0.49%	-8.40%	8.64%	**0.040**	0.011
	MR-OLS	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MR-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-OLS	0.87%	-	0.16%	0.00%	0.89%	-	**93.61%**	-	0.89%	-	-7.14%	-	0.077	-
	MRJD-GARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-
	MRJD-EGARCH	-	-	0.00%	0.00%	-	-	-	-	-	-	-	-	-	-

Next, table 4-11 reports the p-values for the pair-wise modified Diebold-Mariano (MDM) test, between the model that delivers the smallest LF and all those models that pass the first evaluation stage, for the long and the short trading positions, respectively. The null hypothesis of the MDM test is that both the benchmark and the competing models are equally accurate in their VaR forecasts. The null hypothesis is rejected whenever the reported p-value is less than 1%[25]. An asterisk indicates that the competing models are statistically performing equally well for predicting VaR, whereas a double asterisk indicates that the VaR hit series for both competing models is identical and so there cannot be any differentiation between the two. In such cases the p-value is equal to 1 as the null is accepted with 100% confidence. As far as the long trading positions are concerned, according to the reported p-values and for $\alpha=1\%$, it is for the WTI and the Propane markets that the F-EGARCH is statistically superior as a stand-alone model relative to the competing models, and for the HO market that the MCS-MRJD-GARCH model stands out. For all remaining energy markets and the SEI, all the pair wise competing models perform statistically equally well with the model that delivered the lowest LF at the second evaluation stage. In some cases the two competing models are statistically identical, as is the case for example with PJM and the SEI where the benchmarks HMCS-MR-GARCH and HMCS-MR-EGARCH when compared with the HS and the HMCS-MR-GARCH, respectively, seem to be delivering exactly the same statistical accuracy. As far as the short trading positions are concerned and for all energy commodities and the SEI, according to the respective p-values, the null hypothesis cannot be rejected for all competing pairs of models. Again, there are many cases that the two competing models behave statistically the same. For example in the case of the SEI and for the benchmark HMCS-MR-EGARCH model, the null that the two competing models are the same, is respectively accepted with 100% confidence for the comparisons with the F-HS, HS, HMCS-MR-GARCH, and HMCS-MR-OLS models.

[25] The relevant t-stats (MDM-statistics) are also calculated but are not reported in the table because in every case, the outcome is identical to that of the p-values.

Table 4-11: Modified Diebold-Mariano test at a=1%.

The p-values for the pair-wise modified Diebold-Mariano (MDM) test, between the model that delivers the smallest LF and all those models that pass the first evaluation stage, are reported for both the long and the short trading positions, respectively. The null hypothesis of the MDM test is that both the benchmark and the competing models are equally accurate in their VaR forecasts, ie. davg = 0. The null hypothesis is rejected whenever the reported p-value is less than 1% . An asterisk indicates that the competing models are statistically performing equally well for predicting VaR, whereas a double asterisk indicates that the VaR hit series for both competing models is identical and so there cannot be any differentiation between the two. In those cases that the p-value is equal to 1 it means that the hit series is identical for both models, thus the null is accepted with 100% confidence.

Long positions	p-value	Short positions	p-value
Panel A: WTI		**Panel A: WTI**	
F-EGARCH vs F-GARCH	0.00153	MCS-MRJD-GARCH vs MCS-MRJD-OLS*	0.27143
F-EGARCH vs GARCH	0.00106	MCS-MRJD-GARCH vs MCS-MRJD-EGARCH*	0.06714
F-EGARCH vs MCS-MRJD-OLS	0.00001	MCS-MRJD-GARCH vs GARCH*	0.22576
F-EGARCH vs MCS-MRJD-GARCH	0.00003	MCS-MRJD-GARCH vs F-GARCH*	0.12068
F-EGARCH vs MCS-MRJD-EGARCH	0.00002	**Panel B: HO**	
Panel B: HO		MCS-MRJD-OLS vs EGARCH*	0.17246
MCS-MRJD-GARCH vs GARCH	0.00050	MCS-MRJD-OLS vs F-EGARCH*	0.04257
MCS-MRJD-GARCH vs MCS-MRJD-EGARCH	0.00049	MCS-MRJD-OLS vs F-GARCH*	0.11082
MCS-MRJD-GARCH vs MCS-MRJD-OLS	0.00049	MCS-MRJD-OLS vs GARCH*	0.11082
Panel C: GASOLINE		MCS-MRJD-OLS vs F-HS*	0.09640
MCS-MRJD-EGARCH vs HMCS-MR-EGARCH*	0.07456	MCS-MRJD-OLS vs HS*	0.14003
MCS-MRJD-EGARCH vs HMCS-MR-GARCH*	0.07456	**Panel C: GASOLINE**	
MCS-MRJD-EGARCH vs HMCS-MR-OLS*	0.07456	MCS-MRJD-EGARCH vs MCS-MRJD-GARCH**	1.00000
MCS-MRJD-EGARCH vs MCS-MRJD-OLS*	0.02425	MCS-MRJD-EGARCH vs MCS-MRJD-OLS*	0.23883
MCS-MRJD-EGARCH vs MCS-MRJD-GARCH**	1.00000	**Panel D: CS_GASOLINE-WTI**	
Panel D: CS_GASOLINE-WTI		MCS-MRJD-EGARCH vs F-GARCH*	0.27350
MCS-MRJD-EGARCH vs F-EGARCH*	0.04705	MCS-MRJD-EGARCH vs MCS-MRJD-OLS**	1.00000
MCS-MRJD-EGARCH vs F-GARCH*	0.04492	**Panel E: CS_HO_WTI**	
Panel E: CS_HO_WTI		MCS-MRJD-GARCH vs F-EGARCH*	0.14819
F-EGARCH vs F-GARCH**	1.00000	MCS-MRJD-GARCH vs F-GARCH*	0.19136
F-EGARCH vs MCS-MRJD-EGARCH*	0.04541	MCS-MRJD-GARCH vs MCS-MRJD-EGARCH*	0.16611
Panel F: NG		MCS-MRJD-GARCH vs MCS-MRJD-OLS*	0.17455
F-EGARCH vs F-GARCH*	0.02523	**Panel F: NG**	
Panel G: PROPANE		HMCS-MR-EGARCH vs F-EGARCH*	0.32131
F-EGARCH vs F-GARCH	0.00000	HMCS-MR-EGARCH vs F-GARCH*	0.24441
F-EGARCH vs GARCH	0.00000	HMCS-MR-EGARCH vs GARCH*	0.32131
F-EGARCH vs MCS-MRJD-EGARCH	0.00000	HMCS-MR-EGARCH vs HMCS-MR-GARCH**	1.00000
F-EGARCH vs MCS-MRJD-GARCH	0.00000	HMCS-MR-EGARCH vs HMCS-MR-OLS**	1.00000
F-EGARCH vs MCS-MRJD-OLS	0.00000	HMCS-MR-EGARCH vs HS**	1.00000
Panel H: PJM		**Panel G: PROPANE**	
HMCS-MR-GARCH vs EGARCH*	0.02825	GARCH vs F-GARCH*	0.44775
HMCS-MR-GARCH vs F-EGARCH*	0.01493	GARCH vs MCS-MRJD-EGARCH*	0.68379
HMCS-MR-GARCH vs GARCH*	0.05711	GARCH vs MCS-MRJD-GARCH*	0.98214
HMCS-MR-GARCH vs F-GARCH*	0.06827	GARCH vs MCS-MRJD-OLS*	0.70167
HMCS-MR-GARCH vs HS**	1.00000	**Panel H: PJM**	
HMCS-MR-GARCH vs F-HS*	0.11287	HMCS-MR-EGARCH vs EGARCH*	0.61715
HMCS-MR-GARCH vs V&C*	0.08707	HMCS-MR-EGARCH vs F-GARCH*	0.53082
HMCS-MR-GARCH vs HMCS-MR-EGARCH*	0.16148	HMCS-MR-EGARCH vs HS**	1.00000
HMCS-MR-GARCH vs HMCS-MR-OLS*	0.16148	HMCS-MR-EGARCH vs F-HS*	0.22927
HMCS-MR-GARCH vs HMCS-MRJD-EGARCH*	0.08707	HMCS-MR-EGARCH vs V&C*	0.50022
HMCS-MR-GARCH vs HMCS-MRJD-GARCH*	0.08707	HMCS-MR-EGARCH vs HMCS-MR-GARCH**	1.00000
HMCS-MR-GARCH vs HMCS-MRJD-OLS*	0.08707	HMCS-MR-EGARCH vs HMCS-MR-OLS**	1.00000
HMCS-MR-GARCH vs MCS-GBM*	0.08707	HMCS-MR-EGARCH vs HMCS-MRJD-EGARCH*	0.51731
Panel I: SEI		HMCS-MR-EGARCH vs HMCS-MRJD-GARCH*	0.51731
HMCS-MR-EGARCH vs EGARCH*	0.14987	HMCS-MR-EGARCH vs HMCS-MRJD-OLS*	0.51731
HMCS-MR-EGARCH vs F-EGARCH*	0.14888	**Panel I: SEI**	
HMCS-MR-EGARCH vs F-GARCH*	0.15747	HMCS-MR-EGARCH vs F-EGARCH*	0.09881
HMCS-MR-EGARCH vs HS**	1.00000	HMCS-MR-EGARCH vs F-GARCH*	0.12346
HMCS-MR-EGARCH vs F-HS*	0.15747	HMCS-MR-EGARCH vs F-HS**	1.00000
HMCS-MR-EGARCH vs GARCH*	0.14888	HMCS-MR-EGARCH vs HS**	1.00000
HMCS-MR-EGARCH vs HMCS-MR-GARCH**	1.00000	HMCS-MR-EGARCH vs HMCS-MR-GARCH**	1.00000
HMCS-MR-EGARCH vs HMCS-MR-OLS*	0.15747	HMCS-MR-EGARCH vs HMCS-MR-OLS**	1.00000

HMCS-MR-EGARCH vs HMCS-MRJD-EGARCH*	0.10276
HMCS-MR-EGARCH vs HMCS-MRJD-GARCH*	0.10276
HMCS-MR-EGARCH vs HMCS-MRJD-OLS*	0.10276
HMCS-MR-EGARCH vs MCS-GBM*	0.10276

In addition, table 4-12 reports the p-values for the White's (2000) Reality Check (RC) test, between the model that delivers the smallest LF (benchmark) and all those models that pass the first evaluation stage, for both long and short trading positions. The null hypothesis states that none of the models is better than the benchmark, i.e. there is no predictive superiority over the benchmark itself. Hence, whenever the null hypothesis is accepted it means that there is no competing model that performs better in terms of its VaR forecasting ability than the benchmark model. The null hypothesis is rejected whenever the reported p-value is less than the conventional level of significance of 1%. For the long positions, the null cannot be accepted for Gasoline, the crack spread of HO with WTI, PJM, and the SEI as there can be at least one model that performs equally well or better than the benchmark model. For the WTI, NG, Propane, the crack spread of Gasoline with WTI, and HO markets there is strong evidence that the benchmark model is indeed the best in terms of its VaR performance across the competing models; the F-EGARCH for the former four markets and the MCS-MRJD-GARCH for the latter. As for the short positions, the null cannot be rejected in all cases but three. It is only for the WTI, HO and Gasoline that the benchmark model is not the best performing one according to the reported RC p-values. On the other hand, based on the reported RC p-values, for the two crack spreads of Gasoline and HO with WTI, the Propane, NG, PJM, and the SEI, the benchmark model is indeed the best performing one; that is the MCS-MRJD-EGARCH, MCS-MRJD-GARCH, GARCH, and HMCS-MR-EGARCH for the latter three markets respectively. The results from the RC test indicate that for the long trading positions there is mixed evidence as to which model performs better in terms of its VaR forecasting ability. However, for the short trading positions it is clearer from the results that the proposed MC Simulation and the Hybrid MC-HS methodologies produce a better VaR performance compared to the more traditional ARCH type and Historical Simulation methodologies.

Table 4-12: White's Reality Check at a=1%

The p-values for the White's (2000) Reality Check (RC) test, between the model that delivers the smallest LF (benchmark) and all those models that pass the first evaluation stage, are reported for both long and short trading positions, respectively. The null hypothesis states that none of the models is better than the benchmark, i.e. there is no predictive superiority over the benchmark itself. Hence, whenever the null hypothesis is rejected it means that there is no competing model that performs better in terms of its VaR forecasting ability than the benchmark model. The null hypothesis is rejected whenever the reported p-value is less than the conventional level of significance of 1%.

Long positions	p-value	Short positions	p-value
Panel A: WTI		**Panel A: WTI**	
F-EGARCH	0.88904	MCS-MRJD-GARCH	0.00520
Panel B: HO		**Panel B: HO**	
MCS-MRJD-GARCH	0.17131	MCS-MRJD-OLS	0.00049
Panel C: GASOLINE		**Panel C: GASOLINE**	
MCS-MRJD-EGARCH	0.00169	MCS-MRJD-EGARCH	0.00005
Panel D: CS_GASOLINE-WTI		**Panel D: CS_GASOLINE-WTI**	
MCS-MRJD-EGARCH	0.01343	MCS-MRJD-EGARCH	0.04616
Panel E: CS_HO_WTI		**Panel E: CS_HO_WTI**	
F-EGARCH	0.00024	MCS-MRJD-GARCH	0.92270
Panel F: NG		**Panel F: NG**	
F-EGARCH	0.51461	HMCS-MR-EGARCH	0.04111
Panel G: PROPANE		**Panel G: PROPANE**	
F-EGARCH	0.99819	GARCH	0.76569
Panel H: PJM		**Panel H: PJM**	
HMCS-MR-GARCH	0.00178	HMCS-MR-EGARCH	0.02176
Panel I: SEI		**Panel I: SEI**	
HMCS-MR-EGARCH	0.00801	HMCS-MR-EGARCH	0.09610

Finally, table 4-13 summarises the VaR models that have been shortlisted as being the best for predicting VaR for each energy market and the SEI, following the proposed back-testing methodology. Panels A and B show the results for the long and the short trading positions respectively. In both panels, the first two columns list all the models that have successfully passed all three statistical tests, i.e. the first evaluation stage. Next, the remaining columns in each panel report only those VaR models that deliver the lowest LF, alongside those models that the MDM test identifies that their hit series is identical. According to the implemented two stage back-testing procedure, at the 1% significance level and for the short positions, it is the MC simulation and the Hybrid MC-HS methods from which the preferred models for estimating the VaR are short-listed; this finding is consistent with all energy markets and the SEI. As for the long trading positions results are mixed. On the one hand, it is again the MC simulation and the Hybrid MC-HS methods that are the best choices for the HO, Gasoline, CS-Gasoline-WTI, PJM, and the SEI. On the other hand, it is the ARCH-type models, and more specific the F-GARCH and F-EGARCH models, that stand out as the best VaR modelling options for the WTI, CS-HO-WTI, NG, and Propane markets.

Therefore, whenever a risk manager wants to choose a single approach for calculating the VaR for all energy commodities that he/ she holds, as it is usually the case in practice, the results show that the MC simulations and the Hybrid MC-HS approaches proposed in this thesis are the most reasonable, efficient, and consistent candidates. The findings of this research have important implications for regulatory and policy-making purposes as the decision making bodies can reconsider the commonly used VaR models and establish an industry-wide methodological approach for calculating and back-testing the VaR in the energy markets. The proposed MC simulation and the Hybrid MC-HS models, in combination with the proposed selection procedure, have the potential of becoming common practise in the energy industry.

Table 4-13: Summary of models that pass the back-testing methodology in each stage at a=1%.

The VaR models that have been shortlisted as being the best for predicting VaR for each energy market and the SEI, following the proposed back-testing methodology, are summarised below. Panels A and B show the results for the long and the short trading positions, respectively. In both panels, the first two columns list all the models that have successfully passed all three statistical tests, i.e. the first evaluation stage. Next, the remaining columns in each panel report only those VaR models that deliver the lowest LF on the basis of the MDM tests, alongside those models that the MDM test identifies that

Panel A: Long positions

1st stage		2nd stage
Panel A: WTI		
F-EGARCH	MCS-MRJD-OLS	F-EGARCH
F-GARCH	MCS-MRJD-GARCH	
GARCH	MCS-MRJD-EGARCH	
Panel B: HO		
MCS-MRJD-GARCH	MCS-MRJD-EGARCH	MCS-MRJD-GARCH
GARCH	MCS-MRJD-OLS	
Panel C: GASOLINE		
MCS-MRJD-EGARCH	HMCS-MR-OLS	MCS-MRJD-EGARCH
MCS-MRJD-OLS	HMCS-MR-EGARCH	MCS-MRJD-GARCH
MCS-MRJD-GARCH	HMCS-MR-GARCH	
Panel D: CS_GASOLINE-WTI		
MCS-MRJD-EGARCH	F-GARCH	MCS-MRJD-EGARCH
F-EGARCH		
Panel E: CS_HO_WTI		
F-EGARCH	MCS-MRJD-EGARCH	F-EGARCH
F-GARCH		F-GARCH
Panel F: NG		
F-EGARCH	F-GARCH	F-EGARCH
Panel G: PROPANE		
F-EGARCH	MCS-MRJD-EGARCH	F-EGARCH
F-GARCH	MCS-MRJD-GARCH	
GARCH	MCS-MRJD-OLS	
Panel H: PJM		
HMCS-MR-GARCH	V&C	HMCS-MR-GARCH
EGARCH	HMCS-MR-EGARCH	HS
F-EGARCH	HMCS-MR-OLS	
GARCH	HMCS-MRJD-EGARCH	
F-GARCH	HMCS-MRJD-GARCH	
HS	HMCS-MRJD-OLS	
F-HS	MCS-GBM	
Panel I: SEI		
HMCS-MR-EGARCH	HMCS-MR-GARCH	HMCS-MR-EGARCH
EGARCH	HMCS-MR-OLS	HS
F-EGARCH	HMCS-MRJD-EGARCH	HMCS-MR-GARCH
F-GARCH	HMCS-MRJD-GARCH	
HS	HMCS-MRJD-OLS	
F-HS	MCS-GBM	
GARCH		

Panel B: Short positions

1st stage		2nd stage
Panel A: WTI		
MCS-MRJD-GARCH	GARCH	MCS-MRJD-GARCH
MCS-MRJD-OLS	F-GARCH	MCS-MRJD-OLS
MCS-MRJD-EGARCH		MCS-MRJD-EGARCH
		GARCH
		F-GARCH
Panel B: HO		
MCS-MRJD-OLS	GARCH	MCS-MRJD-OLS
EGARCH	F-HS	EGARCH
F-EGARCH	HS	F-EGARCH
F-GARCH		F-GARCH
		GARCH
		F-HS
		HS
Panel C: GASOLINE		
MCS-MRJD-EGARCH	MCS-MRJD-OLS	MCS-MRJD-EGARCH
MCS-MRJD-GARCH		MCS-MRJD-GARCH
Panel D: CS_GASOLINE-WTI		
MCS-MRJD-EGARCH	MCS-MRJD-OLS	MCS-MRJD-EGARCH
F-GARCH		MCS-MRJD-OLS
Panel E: CS_HO_WTI		
MCS-MRJD-GARCH	MCS-MRJD-EGARCH	MCS-MRJD-GARCH
F-EGARCH	MCS-MRJD-OLS	
F-GARCH		
Panel F: NG		
HMCS-MR-EGARCH	HMCS-MR-GARCH	HMCS-MR-EGARCH
F-EGARCH	HMCS-MR-OLS	HMCS-MR-GARCH
F-GARCH	HS	HMCS-MR-OLS
GARCH		HS
Panel G: PROPANE		
GARCH	MCS-MRJD-GARCH	GARCH
F-GARCH	MCS-MRJD-OLS	
MCS-MRJD-EGARCH		
Panel H: PJM		
HMCS-MR-EGARCH	HMCS-MR-GARCH	HMCS-MR-EGARCH
EGARCH	HMCS-MR-OLS	HS
F-GARCH	HMCS-MRJD-EGARCH	HMCS-MR-GARCH
HS	HMCS-MRJD-GARCH	HMCS-MR-OLS
F-HS	HMCS-MRJD-OLS	
V&C		
Panel I: SEI		
HMCS-MR-EGARCH	HS	HMCS-MR-EGARCH
F-EGARCH	HMCS-MR-GARCH	HMCS-MR-GARCH
F-GARCH	HMCS-MR-OLS	HMCS-MR-OLS
F-HS		F-HS
		HS

4.6. Conclusion

This chapter proposes and compares a set of models for estimating the VaR of eight spot energy markets that trade futures contracts on NYMEX, and of the constructed Spot Energy Index, for both long and short trading positions, at the 1% significance level. The two proposed VaR methodologies are a MC simulation approach, and a Hybrid MC with Historical Simulation approach, both assuming various processes for the underlying spot prices. Next, a two-stage evaluation and selection process is applied, combining statistical and economic measures, to choose amongst the competing VaR models. The results show that, at the 1% significance level, for all commodities and the SEI there is at least one model that passes all three statistical tests with the ARCH type, the MC simulation, and the Hybrid MC-HS models prevailing more. For the entire fuels complex, including the WTI, HO, Gasoline, and the crack spreads with WTI, and for both long and short positions, the MC simulations methodology under the MRJD specifications, followed by the Hybrid MC-HS models pass all three statistical criteria from the first evaluation stage, and at the same time deliver the lowest LF at the second evaluation stage. The only exceptions are the WTI and the CS-HO-WTI just for the long trading positions, with the ARCH-type methodologies delivering the lowest LFs respectively. Therefore, it is concluded that the two former approaches are the most reasonable, efficient, and consistent candidates for calculating the VaR of energy prices, for both long and short positions.

The accurate calculation of VaR measures in the volatile energy markets is important for all market players and for a variety of reasons. First, the spot energy price risk is quantified taking into consideration the occurrence of extreme volatility events and thus at the same time allowing managers to develop efficient hedging strategies to protect their investments. Second, with the proposed VaR model selection process, modelling risk can be minimised as it satisfies strict risk management requirements and control procedures, by reducing the probability of accepting flawed models. Third, quantifying the risk profile of the energy markets, as expressed by the individual spot price series and the SEI, is vital for many hedge fund managers and alternative investors that have recently been following closely and started expanding their presence in the energy markets. Finally, the proposed VaR estimates can be used for setting the margin requirements in the growing energy derivatives market, and more importantly for the energy forwards, futures, and options that are widely used for both hedging and speculation purposes by many industrial players, commodity and investment houses. This can be achieved by adopting the proposed models for their derivative contracts' valuations which, as proved in the previous chapter, are able to describe the energy markets better, exhibiting better explanatory power and goodness of fit. These models incorporate mean-reversion and spikes in the stochastic behaviour of the underlying asset, allowing for a different speed of mean reversion once a jump is identified, while at the same time allowing for time-varying volatility in their specification modelled as a GARCH or an EGARCH process. While risk management clearly did not fully prevent a downside in investment portfolios during the recent economic recession, according to Briand and Owyong (2009) those organisations that had invested in risk management practices prior to the crisis, and acted on their findings, performed significantly better than those that did not.

Moreover, numerous authors argue that it is impossible to constantly beat the market, whereas a buy-and-hold strategy of the market through a market index is the best approach (Andreu and Torra, 2009). Generally, financial portfolio management is implemented by using active or passive strategies. Under the active strategy, the portfolio manager assumes that markets are not perfectly efficient and there is room to exploit any disequilibrium or mispricing; hence, portfolio managers will attempt to pick high performing stocks and/or time their buy/sell decisions in order to outperform the market or other stocks (Beasley et al., 2003). On the other hand, a passive strategy assumes that the market is efficient and cannot be beaten in the long run (Maringer and Oyewumi, 2007); as a result, the main activity of a manager is to achieve the same or at least a very similar return as a specified market index. According to Beasley et al. (2003), active strategies normally have higher fixed and transaction costs[26]. On the contrary, passive strategies can have lower fixed costs and lower transaction costs, with the only disadvantage that if the market/index falls, unavoidably, so will the return obtained from the portfolio index. Taking into account the importance of market indices as benchmarks against which performance is compared, and as essential tools to prove efficiency, this thesis uses the proposed geometric average Spot Energy Index as a benchmark, to test the performance of an innovative tracking investment strategy, where only a subset of stocks from various equity pools is selected optimally with the help of two evolutionary algorithms. The latter strategy is examined in the next chapter.

[26] Fixed costs are mainly associated with payments to the management team. Also, frequent trading involved in active management leads to higher transaction costs compared to a passive strategy.

Chapter 5.

5. Performance replication of the spot energy index with optimal equity portfolio selection

This chapter reproduces the performance of a geometric average Spot Energy Index by investing only in a subset of stocks from the Dow Jones Composite Average, the FTSE 100 and Bovespa Composite indexes, and in two pools including only stocks of the energy sector from the US and the UK respectively. Daily data are used and the index-tracking problem for passive investment is addressed with two innovative evolutionary algorithms; the differential evolution algorithm and the genetic algorithm, respectively. Finally, the performance of the suggested investment strategy is tested under three different scenarios: buy-and-hold, quarterly, and monthly rebalancing; accounting for transaction costs where necessary.

5.1. Introduction

Passive strategies are becoming increasingly popular. According to Konno and Hatagi (2005), almost half the capital in the Tokyo Exchange is subject to passive trading strategies. Empirical evidence seems to support the idea that the passive strategies are better than the active ones in the longer term. Sharpe (1991) argues that on average active managers cannot beat passive strategies and active trading strategies are a zero-sum game, such that some managers win and others lose relative to the return of the market or a particular market sector; consequently, after deducting the fixed and transactions costs, the average return of actively managed portfolios will be less than the average return on passively managed portfolios. Furthermore, more recent studies have shown that passive strategies outperform active strategies on average (Malkiel, 1995; Sorenson et al., 1998; Frino and Gallagher, 2001). In addition, Barber and Odean (2000) find that in active trading strategies the presence of high transaction costs, and sometimes the overconfidence of investors in their predictions, reduces the profits substantially and potentially leads to losses.

One of the most popular forms of passive trading strategies is index tracking. The index tracking method attempts to replicate/ reproduce the performance of an index, in terms of its returns across time. In the attempt to replicate the returns of an index/ portfolio, managers can choose between two ways of doing that. First, with full replication all the stocks in an index are purchased and the index is perfectly reproduced. Nevertheless, this method has some practical limitations/ disadvantages. According to Beasley et al. (2003), replicating fully an index would entail frequent revisions[27] in order to reflect the updated weightings in the index, leading to high transaction costs. What is more, one-to-one replication suffers from the disadvantage that some stocks can be very illiquid. For these reasons, many passive strategy managers prefer alternatively the partial replication. In this way, managers ultimately hold these stocks in their portfolios which they consider to be replicating the index most effectively.

It is well documented in the literature that investors can benefit by getting exposure in commodities as part of their long-term asset allocation plan. Over the past decade impressive gains have been witnessed in commodity prices, with this pattern accelerating in the last few years. This has attracted investors' attention and led to an impressive growth of index

[27] Revisions can occur for a number of reasons including additions or deletions, mergers, splits, and dividends.

investing in the commodity markets. In general there are three major ways of investing in a commodity index; first, by choosing an index and replicating it by following the related Rule Book; second, by investing in a fund that replicates the chosen index; finally, the most popular approach lately is by buying shares of an ETF that its strategy is to follow the respective commodity index. This trend has been recognised by investors and prompted them to set-up the first commodity Exchange Traded Fund (ETF) in November 2004[28]. As of January 2010 the market capitalization of that first commodity ETF was exceeding 39 billion US dollars, competing with numerous other commodity-related ETFs established since then. Many other ETFs investing in physical commodities, futures, and commodity-related equities, have followed since then.

Generally, commodities are seen as a hedge against inflation (Bodie, 1983; Gorton and Rouwenhorst, 2006). Though currently inflation is relatively low and stable, mounting worries about potential inflation pressures moving forward can be enticing more investors to the commodities market. In addition, since most energy commodities and especially crude oil are quoted in US dollars, any weakening of the USD against an international basket of major currencies and especially the euro, leads to an appreciation of the energy commodities in dollar terms. This happens on the one hand because demand is global, taking place in an international market scene, reflecting global currency prices, and on the other hand because these energy commodities are used by investors as a hedge against further US dollar weakness and other floating currencies. Moreover, the long lead times to bring additional capacity to satisfy the newly created excess demand for energy commodities, driven by the billions of people entering the global consumer economy, will attract even more investors to the energy commodity markets going forward.

There are many papers applying various momentum and market timing strategies to commodity futures markets, with the findings in the literature suggesting that there is mixed evidence on their performance (see for example, Miffre and Rallis, 2007; Alizadeh et al., 2008; Marshall et al., 2008; Szakmary et al., 2010). In addition, there is a plethora of studies focusing on the effects of oil price changes on the economy (e.g. Hamilton, 2003), on whether oil price risk is priced in stock markets (e.g. Jones and Kaul, 1996), and whether oil prices forecast future stock market returns (e.g. Driesprong et al., 2008). However, the

[28] The first listed commodity ETF was the streetTRACKS Gold Shares ETF, with its sole assets being gold bullion and from time to time cash.

question whether returns of equity portfolios can be used to replicate the performance of physical energy price returns, aggregated in a portfolio and proxied by a spot index, has received almost no attention in the existing literature.

The aim of this chapter is to replicate the unique price/ return behaviour of direct energy commodity investment using equities. The proposed approach is based on previous research findings that in the case of equally weighted long-only portfolios of commodity futures, with a changing composition over the studied period, their statistically significant returns are similar to those of stocks (Bodie and Rosansky, 1980; Fama and French, 1987; Gorton and Rouwenhorst, 2006). In addition, it is documented in the literature that after the 2000s, commodities have gone through a financialization process, exposing them to the wider financial shocks (Tang and Xiong, 2010). The goal is accomplished by applying two very efficient in terms of tracking error strategies, the Differential Evolution Algorithm (DE) and the Genetic Algorithm (GA), to solve the index tracking problem in the energy markets as represented by the constructed Spot Energy Index (hereafter named SEI). Low tracking error strategies provide several advantages to investors; they result in better diversified portfolios, make the long-only constraint of a fund manager less binding, and in general tend to provide higher returns for various equity strategies. As of 2005, more than 50% of the trading volume on NYSE was performed using some form of program trading strategies (Lamle and Martell, 2005).

More specifically, the performance of the SEI is reproduced by investing in a small basket of stocks picked either from the stocks comprising three well known financial indexes, or from two pools of energy related stocks. In particular, the cases of the US, UK and Brazilian investors are considered under the assumption that they want to invest in the SEI and prefer to access only their local stock markets due to cost savings and/or better knowledge of the respective markets. They represent two developed and one developing stock market, with the latter having its unique energy significance in the global scene. The recent reforms and regulations that took place in Brazil brought transparency, sophistication and additional liquidity to its financial markets. It is this reliability in the Brazilian stock market data that led to the selection of this market for testing and implementing the proposed investment strategy. The lack of transparency and liquidity in other emerging stock markets, which have a large number of commodity related firms listed, as for example in Russia, can be questionable as it could lead to obscure datasets. In addition, while recently many developed countries have sputtered amid weak economic growth, Brazil has continued to thrive, given its rich reserve of natural resources and growing middle class, becoming the fifth-largest economy in the world.

In addition, it is well documented in the literature that energy prices affect national economies and have a different impact on the various business sectors. As Hammoudeh et al. (2004) point out in their study, the oil related industries are amongst the most affected sectors, with higher oil prices having a positive impact on most companies. Oil, and in effect energy prices, affect companies' earnings and their bottom lines, thus having an immediate effect on their stock prices. Hence, based on intuition and previous research findings, the two pools of energy related stocks used in the analysis should perform very well in tracking the SEI. Moreover, the three non-energy specific stock pools are used as a relative performance measure, as there is a possibility that the stocks of various companies operating in other, non-energy related industries to be directly affected by the movements in energy prices, thus making them a good selection for constructing the portfolios that track the SEI. The methodology implemented can track the SEI or any other benchmark index by investing in a basket of stocks that each of the evolutionary algorithms will determine. Baskets of maximum 10, 15 and 20 stocks are selected from the following stock pools: Dow Jones Composite Average, FTSE 100, Bovespa Composite, and two unique pools of energy related stocks from the US and the UK stock markets respectively. The proposed methodology allows investors to be more comfortable with their investment selection since this is drawn out of a stock market that they are more familiar with.

Hence, the first contribution of this chapter in the literature is that the index tracking problem in the energy commodities market is addressed and both the DE and GA are applied. Second, investors are provided with the opportunity to invest in the energy spot markets by choosing stocks from a specific domestic equity market which could appeal more to their investing criteria/ preferences. Third, by tracking the performance of the energy sector with stocks selected by two innovative evolutionary algorithms, a cost effective implementation and true investability is promoted for the popular segment of energy style investors. Barberis and Sheleifer (2003) argue that style investing is attractive mostly because of the fact that institutional investors act as fiduciaries and thus they must follow systematic rules of portfolio allocation, and because of its simplified performance evaluation process. However, there are many funds that cannot invest in commodities directly as in the case of pension funds, where governments in their effort to protect peoples' savings strictly regulate the industry by placing stringent restrictions on the types of assets held. Usually futures contracts and other derivative products in alternative investments such as commodities are excluded from their portfolios (Nijman and Swinkels, 2003). Nevertheless, by following the proposed investment strategy and investing in stock portfolios selected by the evolutionary algorithms used in this thesis, these funds could now participate in the energy markets by investing in an ETF that would track the performance of the SEI. Fourth, given the importance of equities in a multi-asset class portfolio, by choosing those stocks that can track the SEI, the selected equity portfolios are indirectly insulated from inflation; a key consideration among investors and fund managers in an uncertain economic environment. In their investigation over the period 1972-2001, Nijman and Swinkels (2003) find that investors with liabilities indexed to the interest rate and inflation, such as insurance companies and pension funds, can significantly increase their risk-return trade-off through commodity investment because of the positive relation of commodities with inflation. Fifth, it is the first time that a broad energy index incorporates in its calculation electricity market prices, thus reflecting the full spectrum of energy commodities and their by-products besides the commonly used crude oil and its refined fuels. Finally, this chapter contributes to the existing literature by investigating three different investment strategies during the three year out-of-sample period, buy-and-hold, quarterly, and monthly rebalancing; accounting for transaction costs where necessary.

Although the SEI represents the economic importance of the energy group of commodities to the global economy, it primarily serves as a performance benchmark given the limited ability for a direct investment. However, the proposed approach provides investors with an option to track the performance of this Spot Energy Index using a basket of equities that are liquid and fully investable. This allows investors to get closer to the underlying commodity market price trends, something they cannot achieve using a futures price index. Historically, futures index returns have lagged price index returns, with this decoupling of performance being a constant frustration for index investors. For comparison reasons the performance of two well established energy excess return indexes is reported, namely the Dow Jones–UBS Energy Sub-Index and the Roger's Energy Commodity Index, against the performance of the constructed SEI and the selected portfolios.

This chapter's findings have several positive implications for investors. They provide a low cost – compared to actively managed funds – means of accessing the energy spot markets. In particular, sector rotation investment managers can benefit from the findings of this thesis. By tactically shifting assets, they can over- or under-weigh specific sectors according to their due diligence, economic outlook or market objective. Diversification is another important implication. Instead of taking concentrated risks by purchasing individual stocks, the investors can own our proposed baskets and at the same time avoid the diligent attention that individual stocks require. Furthermore, investors who on the one hand want to participate in the performance of the volatile spot energy sector, but on the other hand do not want the high risk exposure of holding the individual energy commodity, can invest in the selected stock baskets that exhibit substantially lower volatility. Finally, investors that cannot physically hold the energy commodities can benefit from the selected equity baskets that allow for both long and short position to be taken. Most commodity trading advisors and commodity pool operators use investment strategies that can be long-only or systematic long/short, using leverage to take the short positions. The latter strategy assumes that investors take opposite positions than those taken by commercial hedgers (Jaeger et al., 2002). So an effective index tracking strategy, as the one proposed in this chapter, should allow for both the replication of the performance benchmark index, and the implementation of this long/short strategy that can significantly improve the risk/ return profile of traditional asset portfolios.

The structure of this chapter is as follows. Section 2 presents a literature review on energy commodity indexes and the relation between commodities and equities. Section 3 gives an explanation of the constructed energy spot index and the data used in the analysis. In section 4, the DE and GA are explained, with the problem formulation also being described. Section 5 offers the empirical results of the study and, finally, section 6 concludes the chapter.

5.2. Energy commodity investing

5.2.1. Energy indexes

There are two ways of investing in energy commodities. The first is the direct physical investment that includes all relevant costs for maintaining and managing the inventory. The second is the indirect investment via equity or debt ownership of energy companies and utilities, engaged in oil exploration, production, refining, marketing etc. However, in recent years there has been an increasing number of direct energy commodity-based products available to investors such as the respective energy futures contracts that require constant active management, and the energy commodity indexes. There is a large number of mutual funds, hedge funds, Exchange Traded Funds (ETFs), Exchange Traded Notes (ETNs) and OTC return swaps that follow the energy sector through index investing. In fact, in the US alone, assets allocated to commodity index strategies via futures contracts has risen from $13 billion in 2003 to $260 billion as of March 2008, with an estimated 70 percent of these funds invested in the energy sector (Hamilton, 2009b). From the total of commodity index investing in US exchanges alone, about 42% is conducted by institutional investors (pension and endowment funds), 25% by retail investors (ETFs, ETNs and similar exchange-traded products), 24% by index funds (a client/ counterparty with a fiduciary obligation to match or track the performance of a commodity index), and 9% by Sovereign wealth funds (CFTC, 2008).

Commodity indexes attempt to replicate the returns equivalent to holding long positions in various commodities markets without having to actively manage the positions. Being uncorrelated with the returns of traditional assets such as stocks and bonds, commodity index investments' returns provide a significant opportunity to reduce the risk of traditional investment portfolios; thus explaining the economic rationale for including a commodity index investment in institutional portfolios such as those of pension funds and university endowments. Currently there are more than ten publicly available futures' indexes, with different risk and return profiles, offering exposure to commodity markets; each of these indexes also offers specific exposure to certain commodity sectors via their traded sub-indexes. The variations in commodity index performance across indexes and during different market conditions lie with the differences in the construction methodology of each index. The main differentiations relate to the index sectors' composition, constituent commodities selection, rolling and rebalancing strategy, which are both crucial and apply only for futures indexes, and the methodology used for calculating the constituents' respective weights. The later has been an important determinant of the indexes' performance, especially with the recently large weight allocations towards the energy sector across all indexes (AIA, 2008). This remark strengthens the approach of this chapter that focuses only on the energy sector which has recently drawn the most activity in index investing. Another issue that complicates the historical analysis of commodity futures index returns is the lack of a universal way to define their composition, because commodities cannot have a market capitalization-based portfolio weighting scheme. That is because at any time, the value of all open long futures contracts is offset by the value of the open short futures contracts (Black, 1976).

There are several risks and disadvantages associated with futures' based commodity indexes. In the case of a futures index, unlike a passive equity portfolio which entitles the holder to a continuing stake in a company, commodity futures contracts specify a certain date for the delivery of the physical commodity. In order to avoid the delivery process and maintain a long futures position, a passive futures portfolio requires regular transactions; nearby contracts must be sold and contracts with later deliveries must be purchased. This process is referred to as "rolling". The difference between the prices of the two contracts, the nearby and the more distant delivery one, is called the "roll yield". Even though the term structure of commodity prices has historically been an important driver of realised commodity futures' excess returns, there is no guarantee that the term structure will remain the same in the future. Also, there is a possibility that the futures term structure of an individual commodity be, on average, in backwardation, yet the particular contract that an index mechanically rolls into might be in contango. When commodity markets are in contango this could result in negative roll yields that would adversely affect the value of the futures index. These negative roll yields can significantly decrease the value of the futures index over time when the nearby contracts or spot prices of the underlying commodities are stable or increasing. Also, in the opposite scenario of decreasing spot prices, the value of the futures index can significantly decrease when some or all of the constituent commodities are in backwardation.

Furthermore, although most of the energy commodities have liquid futures contracts with expiration every month, there are some that expire less frequently, thus rolling forward can be more costly and vulnerable to longer duration and smaller liquidity. Moreover, Gorton and Rouwenhorst (2006) find that commodity futures contracts become illiquid in the delivery month as most traders avoid delivery of the physical commodities. In addition, the explicit rolling procedure that needs to be used when tracking a commodity futures index is another major disadvantage. Any transparent commodity futures index publishes the specific rules of rebalancing making them available to all market participants. This means that other traders and speculators can take advantage of these known future transactions mandated by those rules. Under the prevailing trend of these index funds to constantly grow in size, they will only become more vulnerable to such trading exploitation.

In addition, external market and macroeconomic factors can have a major impact on a futures index. The market prices of the index's components may rapidly fluctuate due to changes in supply and demand relationships, and due to other numerous factors such as weather, major political and economic events, technological developments, fiscal and monetary programs. Recently, even the performance of the equities markets has become a significant factor affecting the performance of commodity indexes, especially when the index holds large positions of illiquid contracts or maturities. It has been observed that during periods of steep equity market movements there is a tendency of aggressive buying or selling of commodity indexes (Tang and Xiong, 2010). Investors tend to rebalance the mix of their portfolios between equities and commodities, either for hedging or speculating purposes, or because of their view of the market being short- or long-term. Kyle and Xiong (2001), argue that investors with a short term strategy trade more aggressively against noise trading than those with a long term strategy. All these factors can affect the spot prices of the physical commodities, the underlying of the futures contracts, causing the prices and the volatilities of the components of the index to fluctuate in inconsistent directions and at inconsistent rates. This could quickly lead specific trades against the investor, resulting in a loss of the initial deposit required before being able to close the position.

Moreover, suspension or disruptions of market trading in the commodities futures markets could adversely affect the value of a futures index. Such events that disrupt the functionality of the futures markets, like lack of liquidity, replacement or delisting of a futures contract, changes in the quality specifications of the underlying physical commodities, increased participation of speculators, governmental regulation and intervention, adversely affect a futures commodity index. In fact, the recent increase in volume on the buy side of the futures contracts, in its major part to support index investing, is argued that has an apparent effect on commodity prices drifting them away from their fundamental value and creating a speculative price bubble; a conclusion that can lead to increased government regulation on futures markets. Hamilton (2009a) suggests that speculative investing in oil futures contracts contributed to the oil shock of 2007-08. The steep decline in short-term interest rates in 2008 resulted in negative real interest rates that in turn attracted a great deal of investment in physical commodities, and thus fuelled commodity speculation, especially for crude oil and other energy products (Frankel, 2008).

One can argue that this financialization of commodities introduced a speculative bubble in the price of physical energy commodities, especially crude oil, which subsequently burst. Moreover, in the case of pension funds where governments in their effort to protect people's savings strictly regulate the industry, there are stringent restrictions on the types of assets held by a fund. Usually, futures contracts and other derivative products in alternative investments such as commodities are excluded from their portfolios (Nijman and Swinkels, 2003). Speculation in the commodities markets has been in the centre of a heated debate in the past few years amongst industry and policy circles, on whether it is the driver of excessive increases and the resulted excessive price volatility in the energy and food markets. Following these debates, there have been increasing calls for a more stringent supervision of the energy markets, and in particular for their paper markets, from both the industry's bodies as well as international governments.

The abovementioned risks and disruptions can be avoided when following the investment strategy proposed, by using as a performance benchmark for the energy markets the SEI which allows investors to get closer to the underlying commodity price trends, and by investing in the selected equity portfolios. Using the evolutionary algorithms and the methodology suggested in this chapter, stock investors can optimally select their portfolios for tracking the SEI without spending time, effort, and money, trying to identify which stocks can simultaneously act as a profitable investment and a good commodity play.

5.2.2. Commodities and their relation to equities

Kilian (2009) finds that all major real oil price increases since the mid-1970s can be attributed to increases in global aggregate and/or oil-specific demand, and much less to disruptions of crude oil production. Even when political events affect the oil prices, like the Persian Gulf War, it is mostly the increased sudden demand for oil, triggered by fears for the future oil supply, which drives oil prices and not the actual disruptions in oil supply. In the same lines, Hamilton (2009a) finds that the run-up in oil prices of 2007-08 should be attributed to the strong demand for crude oil in combination with a stagnating world production. From an asset-only perspective, previous research suggests that depending on investors risk tolerance, commodities as proxied by cash-collateralized commodity futures, should be about a quarter of investors' portfolios in their strategic, long-term, asset allocation (Anson, 1999; Jensen et al., 2000).

In addition, Hong et al. (2007) argue that the returns of a number of industry stock portfolios, including that of petroleum, which are informative about macroeconomic fundamentals, can forecast the returns of the aggregate stock market with a lead of up to two months. They also find that high returns for some industries, including that of petroleum, mean bad news for future economic activity and the aggregate stock market. In addition, Driesprong et al. (2008) find that a rise in oil prices significantly lowers future stock market returns, especially for the markets of those countries classified as net energy importers, and the world market index. They also suggest that investors tend to underestimate the direct economic effect of oil price changes on the economy and thus act with a delay. Their conclusion is strengthened by the fact that this under-reaction is less pronounced in the oil-related equity sectors, where market players are more informed and aware of the economic consequences of oil price changes.

Findings by Erb and Harvey (2006) suggest that portfolios of commodity futures can have equity-like returns if a high enough diversification return can be achieved, or if the portfolio exposures are skewed toward contracts that are more likely to have positive roll or spot returns in the future[29]. Gorton and Rouwenhorst (2006) construct a fully-collateralized commodity futures index and conclude that historically, between 1959 and 2004, their index has a similar risk/ return performance to equities, using the S&P500 as a proxy. They also find that correlation between the returns of stocks and bonds and those of the commodity futures is negative; a conclusion that can be attributed to the different behaviour that the various asset classes exhibit over the business cycle. In contrast, Schneeweis and Spurgin (1997) conclude that over the period January 1987 to February 1995, commodity and managed futures indexes have sources of risk and return that are distinct from indexes of traditional assets such as stocks and bonds. Nonetheless, they also find that the unique construction methodology of each index results in differential return correlation with alternative assets, making each index very useful as a performance benchmark for unique portfolios.

Research evidence suggests that before the 2000s commodity indexes had negative correlation with equities, e.g., Greer (2000), Gorton and Rouwenhorst (2006), and Erb and Harvey (2006). However, after the 2000s, commodities were heavily promoted as a new asset class, with various instruments based on commodity indexes attracting billions of dollars from wealthy individuals and institutions, resulting in a financialization process that exposed commodities to the wider shocks of financial markets, as shown in Tang and Xiong (2010). The latter authors also find that this exposure gradually increased, especially after 2004, with

[29] The diversification return is defined as the synergistic benefit of combining two or more assets to reduce variance, enhanced when the portfolio is rebalanced. Roll returns can originate from an upward- or downward-sloping term structure of the individual futures prices.

the spill-over effects of the recent financial crisis contributing to the subsequent large increase of commodity price volatility. Equities and other financial assets mainly derive their value from future cash flows, whereas commodities, being real assets, derive their value from physical supply and demand conditions. Despite this fundamental difference between equities and commodities, the need of commodity producers and consumers to share price risk with the broader investment community was the main driver of the resulted integration of commodities and financial markets.

Why, especially in recent years, are commodities expected to behave more like financial assets? This question can be answered with the following arguments: First, taking into consideration that commodity index investors have a big impact into commodities prices it can be assumed that the remaining participants, such as commercial hedgers and speculators, cannot fully absorb the price impact (Tang and Xiong, 2010). Second, it is known that any shocks affecting the market-wide risk premium, subsequently, affect all financial assets to a varying degree (e.g., Cambell and Cochrane, 1999). It is thus valid to argue that, as commodities become more and more integrated with the financial markets, they should also be affected. Third, when price shocks in one asset occur, by rebalancing his/ her portfolio, the shocks spill-over to the other assets that the marginal investor holds (Kyle and Xiong, 2001). Hence, commodity index investors that usually hold additionally large positions in stocks are exposed to stock market shocks when they reallocate their funds between commodities and stocks. Fourth, Barberis and Shleifer (2003) find that each asset of a certain class is exposed to shock spillovers from other assets in the same class. Therefore, according to Tang and Xiong (2010), individual commodities' prices are exposed to both the shocks to those commodities that participate in the indexes held by index investors, and, to a certain degree, the shocks to off-index commodities. Finally, all non-US commodity index investors are also exposed to exchange rate shocks, as all commodity indexes are denominated in US dollars.

When making portfolio allocation decisions, most investors categorize assets into broad categories called styles (Barberis and Sheleifer, 2003). Stocks within a particular country, index or industry, value stocks or growth stocks, can all be considered as style examples. While some styles persist over the years, such as government bonds, financial innovation guarantees the appearance of new styles, as is the case for instance with mortgage-backed securities. Simplification and performance evaluation are the two main reasons that individual and institutional investors follow style investing[30]. The former makes the processing of vast amounts of information relatively easy and efficient, whereas the latter can help evaluate money managers relative to a performance benchmark specific to their style (Sharpe, 1992). Energy commodity investing could be considered as a new style investment, with a plethora of funds and ETFs that track passive benchmarks of commodity and energy sector equity indexes. The work of this thesis could motivate investors, private and institutional, to follow the international energy industry, a sector that deserves sole attention. The potential benefits of commodity investments for institutions date at least back to Bodie (1980), and especially in the case of insurance companies and pension funds these benefits are recently pointed out in Nijman and Swinkels (2003). Many new energy commodity ETFs and ETNs[31] have come to the market, making it easier for a retail investor to obtain exposure to commodities. There are various types of these Energy Index Funds either based on the construction type of the fund (single- or multi-contract, long-only or bearish[32]), or based on the energy sector they track (broad energy or sector specific).

These tracking funds have a number of advantages over traditional debt instruments (notes, bonds, certificates). They offer less expensive and less risky investment products, while at the same time providing protection against inflation. Also, they can provide easy access to a broad range of investors, a simple way to manage accounting and disclosure procedures, and can lead to fewer taxes since in many countries index fund returns are treated as capital gains and not as income. An energy ETF can be used by the energy industry market players to complete parts of their existing portfolio or to perform tactical strategies. They can be used for hedging energy investment risk, portfolio diversification, or as a control measure of inflation exposure. To that end, the proposed methodology offers an effective, and at the same time inexpensive way to operate such a fund, giving the full flexibility of any investment style, long or short, that equities can provide.

[30] Style investing is particularly attractive to institutional investors because acting as fiduciaries they must follow systematic rules of portfolio allocation (Barberis and Shleifer, 2003).
[31] An ETN, although it is structured similar to an ETF, exposes the investor to counterparty risk making it a much riskier investment.
[32] Bearish Energy Index Funds have the same structure as bullish (long-only) funds with the major difference that investors are not only allowed to buy the fund, but also to put on a short position (sell the fund).

5.3. Benchmark energy index and equity data

The benchmark index used for the application of the index tracking methodology proposed in this thesis is the Spot Energy Index (SEI), as explained in more detail in chapter 3. The SEI is constructed as an un-weighted geometric average of the individual ratios of current prices of six energy commodities to the base period prices. For the purposes of this chapter, the base date for the SEI is set at January 31, 2006 which is the same date that the equity data sample is obtained. The latter includes daily prices for stocks that are picked from the Dow Jones Composite Average, FTSE 100 and Bovespa Composite indexes; representing two developed and one developing stock market with a distinct significance in the global energy scene. The index is also tracked with portfolios that include stocks from a unique pool of energy related stocks from the US and the UK stock markets, respectively.

The two aforementioned energy related equity pools are used because according to Scholtens and Wang (2008) oil related firms' earnings are more likely to be affected by changes in oil prices, as explained by the highly significant estimated coefficients of the earnings-to-price factor returns for their total oil firms' sample. After employing a multi-factor APT model, Al-Mudhaf and Goodwin (1993) find that oil price changes in a period surrounding the 1973 oil shock can explain the return differences in 29 US oil companies that they examine. In addition, Boyer and Filion (2007) with their APT model also find that stock returns of Canadian oil and gas companies have a significant relationship with oil price changes. The selection of the equities included in the two pools is being made according to the Industry Classification Benchmark (ICB) jointly developed by Dow Jones and FTSE (see appendix 8.1). In the sample used, the two filtered pools include all stocks from the US and UK stock markets that are engaged in the various phases of energy production and processing, listed in the following four sectors: 1) Oil and Gas Producers, 2) Oil Equipment, Services and Distribution, 3) Alternative Energy, and 4) Electricity. After applying the filtering procedure to the US and UK stock markets, two energy-related stock pools are constructed hereafter named US Filter and UK Filter, respectively.

Hence, to test the proposed heuristic approach and the efficiency of both the DE and the GA as index-tracking methodologies, five data sets are selected. All stock prices are closing prices adjusted for capital gains according to the annualised dividend yield, and they are all obtained on daily basis for the period January 31, 2006 to February 1, 2010 from Thomson

Financial Datastream. All stock prices are in US dollars thus reflecting the local currency exchange rate against the USD at every point in time for the period examined. Should a company cease trading due to an event (merger, bankruptcy etc.), within the test period, it is dropped from the sample; that is why the total number of stocks in the FTSE 100 and Bovespa pools is less than the total number of stocks included in each index. Moreover, after adjusting for all US and UK Bank Holidays, 1,008 observations are sorted to calculate daily returns for each stock; in the case of the Bovespa Composite stock prices, the data are adjusted separately for all Brazilian holidays as there are major differences between the local calendar and the US and UK ones. Considering 252 trading days in a calendar year, the heuristic approach is tested under various assumptions by selecting the first year as the in-sample period and the last three years as the out-of-sample period. The final five data sets have the following number of stocks: N=41 (UK Filter), N=53 (Bovespa Composite), N=65 (Dow Jones Composite Average), N=77 (US Filter), and N=97 (FTSE 100 Index). See appendix 8.2 for a detailed list of all stocks used in each pool.

5.4. Methodology

5.4.1. Evolutionary Algorithms

EAs have been applied to numerous optimization problems in business, engineering, cognitive and applied sciences (Goldberg, 1989). More specifically, since the 1980s, a rapid expansion of their practical and theoretical financial applications has been witnessed. Some of the applications include portfolio optimization (Lorashi and Tettamanzi, 1996; Beasley et al., 2003; Chang et al., 2009), insurance risk assessment (Hughes, 1990), technical trading rules and market timing strategies (Bauer, 1994; Neely et al., 1997; Allen and Karjalainen, 1999), time series forecasting and econometric estimation (Marimon et al., 1990; Dorsey and Mayer, 1995; Leinweber and Arnott, 1995; Mahfoud et al., 1997). Primarily, there are four paradigms that can be identified as different techniques that belong to the family of EAs. These are the Genetic Algorithms (Holland, 1962, 1975), Genetic Programming (Koza, 1992, 1994), Evolutionary Strategies (Recheuberg, 1973), and Evolutionary Programming (Fogel et al., 1996).

Evolutionary Algorithms (EAs) are widely used in the operational research literature for solving multi-objective optimization problems (Coello Coello, 1999; Deb, 2001), and have many advantages over traditional operational research techniques (Zitzler and Thiele, 1999).

Issues regarding the convexity, concavity, and continuity or multiple local optima of the objective functions do not need to be taken into consideration. The main feature that differentiates an evolutionary search algorithm from other traditional search algorithms such as random sampling (e.g. random walk) and heuristic sampling (e.g. gradient descent), is that it is population based. Evolutionary algorithms use a population of points to search the space rather than a single point making them superior to random search. They also have the advantage of avoiding the hill-climbing behaviours of gradient-based search algorithms (Sivanandam and Deepa, 2007). Traditional optimization techniques, such as the gradient methods, break down due to their inability to handle the constraint that restricts the number of assets included in the tracking portfolio.

In general, an EA generates a population of potential solutions and evaluates the quality of each one based on a problem-specific fitness function that defines the evolution environment. Because it is this cost function that guides the search, no supplementary knowledge is needed. In addition EAs use probabilistic transition rules rather than deterministic ones, and an encoding of the search space rather than a single point (Kingdon and Feldman, 1995). Using various operators, new solutions are generated by selecting the relatively fit population members and then these are recombined, performing an efficient direct search and thus reducing the uncertainty about the search space. However, EAs do have some limitations like the fact that the user cannot easily incorporate problem-specific information, making them less efficient than special purpose algorithms in well understood domains. Another weakness is that in differentiable problems an EA could prematurely converge, or converge to a non-zero gradient point if there is limited genetic variation left in the population.

Nevertheless, for most real world financial problems, a number of unknown factors affect the multi-objective target functions of large search spaces. These are complex problems characterized by irregular features such as multiple optima, nonlinearities, and discontinuities of the objective function. Many option pricing, trading rules and constrained portfolio optimization problems for which a closed form solution is not available, serve as examples. The ability of the EAs to handle the solutions of these types of problems, and to find the global optimum relatively fast, strengthens the conclusion that they are a powerful and robust optimization technique.

5.4.2. Genetic Algorithm (GA) and Differential Evolution Algorithm (DE)

The most popular technique in evolutionary computation research is the Genetic Algorithm (GA). One of the most important steps of the GA is the selection of the individuals used to produce the successive generations. Any single individual in the population has a chance of being selected at least once in order to be reproduced into the next generation. There are many different schemes and their variations that can be used for the selection process such as the roulette wheel selection, which was the first scheme introduced, the tournament and ranking selection, scaling techniques and elitist models (Goldberg, 1989; Michalewicz, 1994). The genetic algorithm used in this chapter applies the tournament selection scheme that requires only the evaluation function to map the solutions to a partially ordered set, allowing for minimization and negativity. It is used in this thesis, because unlike other more conventional schemes, it does not assign any probabilities. Under this scheme, k individuals are randomly selected from the population, with replacement, with the best individual being selected to participate in the new population; each individual represents a vector of prices. This process is repeated until N individuals are selected.

The next most important step in the GA is to select the scheme of the genetic operators used to provide the building block of the search mechanism. The two basic operators are the mutation and the crossover. In the GA variation applied in this chapter, real valued representations are used for both operators as developed by Michalewicz (1994), the uniform mutation and the arithmetic crossover. Let for every variable j, a_j and b_j be the lower and upper bounds, respectively. Next, the uniform mutation selects a random variable j^* which is set equal to a uniform random number, i.e.:

$$x'_{ij} = \begin{cases} U_j \sim unif\left(a_{j*}, b_{j*}\right), & \text{if } j = j* \\ x_{ij}, & \text{otherwise} \end{cases} \tag{5.1}$$

Under the arithmetic crossover scheme, two complimentary linear combinations of the parents are generated based on the random number r drawn from a uniform distribution $U_i \sim unif(0,1)$. The two new individuals $\bar{X}'$ and $\bar{Y}'$ are created based on the following equations:

$$\bar{X}' = r\bar{X} + (1-r)\bar{Y} \tag{5.2}$$

$$\bar{Y}' = (1-r)\bar{X} + r\bar{Y} \tag{5.3}$$

For each new solution to be reproduced, a pair of "parent" solutions, $\bar{X}'$ and $\bar{Y}'$, is selected from breeding from the pool selected previously. Hence, by producing a "child" solution using the abovementioned methods of crossover and mutation, a new solution is created which generally shares many of the characteristics of its "parents". Finally, the GA moves from one generation to the next, selecting and reproducing parent solutions until a termination criterion is met. For the purposes of this thesis the process is repeated until either the population converges to the global optimum (i.e. the optimum solution that satisfies the criteria set) or the pre-specified maximum number of generations is reached. A more extensive discussion on the genetic algorithms' functionalities, extensions and applications, can be found in Holland (1975), Goldberg (1989), Davis (1991) and Michalewicz (1994).

DE, on the other hand, is one of the latest heuristic approaches which also belongs to the family of Evolutionary Algorithms (EAs) and has been developed by Storn and Price (1995) for solving nonlinear and non-differentiable continuous space functions. DE is a stochastic optimization method which can minimize a function capable for modelling the problem's objectives, while at the same time incorporate all necessary solution constraints. More specifically, DE has the following advantages over rival approaches; fast convergence, use of few control parameters, ability to find the true global minimum irrespective of the initial parameter values, robustness, and ease of use (Storn and Price, 1997). What is more, DE's claimed advantages are apparent when applied to the index tracking problem. Maringer and Oyewumi (2007) show evidence for the latter from the Dow Jones Industrial Average by analysing the financial implication of cardinality constraints for tracking portfolios when using a subset of its components. DE does not use binary encoding or a probability density function to self-adapt its parameters as a simple EA. However, there are modified GAs that use real number representation, similar to the one used in this thesis.

Furthermore, the main difference between the GA and the DE lies on the schemes used for the selection process, the mutation and the crossover operators. In the GA, two parents are selected for crossover and the child is a recombination of the parents, whereas in DE three parents are selected for crossover and the child is a perturbation of one of them (Sarker and

Abbass, 2004). The DE is a self adaptive algorithm, with all possible solutions having the same chance of being selected as parents with no dependence on their fitness value, and at the same time it is also a "greedy" algorithm, whereas only the best new solution and its parent are kept. Comparisons on various benchmark problems show that DE performs better when compared to other evolutionary algorithms (Sarker et. al. 2002, Sarker and Abbass, 2004). DE's proven past performance is the reason why it is used to solve the index tracking problem in this thesis, serving as a comparison methodology next to the modified GA.

There are various approaches with respect to the way mutation is computed and to the type of the recombination operator used to solve the global optimization problem. The general notation, for the variant schemes/ strategies for the DE algorithm as introduced by Storn and Price (1997), is the following: DE/x/y/z where, "DE" stands for Differential Evolution, "x" specifies the methodology used to choose the population vector to be mutated, "y" is the total number of vector differences that contributes to the differential, and "z" indicates the crossover scheme used. In the optimization problem presented in this thesis the following notation is used, with x = rand-to-best, y = 1 and z = exp, identifying the "DE/rand-to-best/1/exp" variant as the most suitable. "Rand-to-best" indicates that the population vectors are selected to compute the mutation values that lie on the line defined by the randomly generated and the best-so-far vectors; "1" is the number of pairs of solutions chosen (how many vector differences contribute to the differential); and finally, "exp" means that an exponential crossover scheme is used. Compared to the basic version of the DE, the aforementioned scheme is used in this thesis because it enhances the greediness of the algorithm by incorporating the current best vector into the scheme.

Definition 1: Let $\mathbf{u}_{ji,G+1}$ be the trial vector, $\mathbf{v}_{ji,G+1}$ the mutant vector, $\mathbf{x}_{ji,G}$ the parent solution from the current generation G, $x_{jr_1,G}$, $x_{jr_2,G}$ and $x_{jr_3,G}$ three randomly chosen integer indexes which are mutually different and also different from the running index i. Define,

Mutation: $v_{ji,G+1} = x_{jr_1,G} + F\left(x_{jbest,G} - x_{jr_1,G}\right) + F\left(x_{jr_2,G} - x_{jr_3,G}\right)$ (5.4)

Crossover: $\mathbf{u}_{ji,G+1} = \begin{cases} \mathbf{v}_{ji,G+1}; & \mathrm{u}_j \le CR \text{ or } j = j_{rand} \\ \mathbf{x}_{ji,G}; & \text{otherwise} \end{cases}$ (5.5)

Selection: $\mathbf{x}_{i,G+1} = \begin{cases} \mathbf{u}_{i,G+1}; & f\left(\mathbf{u}_{i,G+1}\right) \le f\left(\mathbf{x}_{i,G}\right) \\ \mathbf{x}_{i,G}; & \text{otherwise} \end{cases}$ (5.6)

$$
\begin{aligned}
& i = 1,2,...NP;\; r_1, r_2, r_3 \in \{1,2,...NP\} \\
& r_1 \neq r_2 \neq r_3 \neq i;\; NP \geq 4 \\
& j = 1,2,...D;\; \mathrm{u}_j \sim unif[0,1] \\
& G = 1,2,..G_{\max} \\
& CR \in [0,1] \\
& F \in [0,2]
\end{aligned}
$$

where NP is the total number of D-dimensional parameter vectors that represent the population of the available decision variables for each generation, which also remains constant during the minimization process. Also, $\mathbf{x}_{jbest,G}$ is the best solution of the population, CR is the crossover probability that controls the fraction of parameter values that are copied from the mutant, and F is a real and constant factor that controls for the magnitude of the differential variations $\left(x_{jbest,G} - x_{jr_1,G}\right)$ and $\left(x_{jr_2,G} - x_{jr_3,G}\right)$, respectively.

The steps of the DE that describe Definition 1 are the following: The first step is the population structure where a random sample of solution vectors is generated, after both the upper and lower bounds for each parameter are specified. A uniform probability distribution for all random solutions is assumed. Then, for every target vector $\mathbf{x}_{i,G}$ a mutant vector $\mathbf{v}_{i,G+1}$ is generated (eq. 4), which combines other randomly selected population vectors. Compared to the basic version of the DE, the control variable F is introduced twice to enhance the greediness of the algorithm by incorporating the current best vector $\mathbf{x}_{best,G}$ into the scheme. This step is known as “mutation”.

Then as a third step, an index j that contains randomly chosen numbers $\mathbf{u}_j$ from the uniform distribution$[0,1]$, ensures that $\mathbf{u}_{i,G+1}$ gets at least one parameter from $\mathbf{v}_{i,G+1}$. If $\mathbf{u}_j$ is less than or equal to the crossover probability CR, then the mutant vector $\mathbf{v}_{ji,G+1}$ is being mixed with the parameters of another predetermined vector, the solution-parent $\mathbf{x}_{ji,G}$, to produce the so-called trial vector $\mathbf{u}_{ji,G+1}$ (eq. 5); otherwise, the parameter is copied from the target vector $\mathbf{x}_{ji,G}$. Moreover, the trial parameter with the randomly chosen index, j_{rand}, is taken from the mutant vector to ensure that the trial vector does not duplicate $\mathbf{x}_{ji,G}$. This step is known as “crossover”. Finally, during the selection process, to decide whether or not to keep the trial vector $\mathbf{u}_{i,G+1}$ as a member of the generation $G+1$, its cost function is compared with the target vector $x_{i,G}$ using the greedy criterion. If the objective function value of the trial vector $\mathbf{u}_{i,G+1}$ is less or equal to that of the target vector $\mathbf{x}_{i,G}$, then it replaces the target vector in the subsequent generation (eq. 6); otherwise, the parent solution $\mathbf{x}_{i,G}$ is retained. This final step is known as "selection".

As mentioned earlier, in order to use the DE algorithm, it needs to be fine-tuned using just three control parameters; the crossover constant (CR); the weighting factor (F); and the number of parents (NP). The CR parameter is responsible for controlling the influence of the parent on the generation of the offspring, with higher values having a reduced effect. The F parameter controls the influence of the pair of solutions that calculate the mutation value (for the variant specification used in this thesis that includes only one pair[33]). For most optimization problems, as a rule of thumb, F and CR should both be set in the range of [0.5, 1], while NP should be between 5*D and 10*D, where D equals the number of decision variables (in the present case this is the number of available stocks) (Price et al., 2005; Storn and Price, 1997). Based on the aforementioned, the combination of F, CR and NP that is used for the optimization problem solved in this thesis is 0.7, 0.5 and 10*D, respectively. The following table summarizes the parameters used as inputs for both the GA and the DE.

[33] Increasing either the population size or the number of pairs of solutions, in order to compute the mutation values, will increase the diversity of possible movements; hence a balance should be kept to make the algorithm more efficient (Feoktistov and Janaqi, 2004).

Table 5-1: Parameters used as inputs in the algorithms.

Genetic Algorithm (GA)	
Solution representation	Binary with 10 digits
Selection	Tournament - stochastic with replacement
Crossover	Arithmetic - 2 individuals
Crossover probability	0.8
Mutation	Uniform
Mutation probability	0.001
Population size	100N
Number of generations	200
Differential Evolution Algorithm (DE)	
Solution representation	Space vector R^N
Crossover	Exponential
Crossover probability	0.5
Mutation	DE/rand-to-best/1
Mutation constant	0.7
Population size	10N
Number of generations	100

5.4.3. Formulating the objective function and its constraints

To test the performance of the proposed heuristic three different scenarios are examined. In the first one, both algorithms are tested without rebalancing the tracking portfolios for the out-of-sample period; in the second scenario the portfolios are rebalanced quarterly; and finally, in the third scenario, the portfolios are rebalanced on a monthly basis. In both cases of rebalancing, transaction costs are taken into consideration. The main purpose of testing the algorithms under these three scenarios is to examine whether by including additional information in the index-tracking algorithm – by regular rebalancing of the portfolio - is more rewarding than buying the initial selected portfolio and holding it throughout the test period.

For each case examined, N number of stocks are held within the in-sample time period [1,2..,T] and the price of the index tracked. The goal is to create tracking portfolios consisting of maximum K stocks (K<N), and replicate the tracked index during the out-of-sample period [T, T+Δt]. The tracking portfolios are created based on the stocks that the algorithms choose, using every time the available data from the in-sample period. To decide which stocks will form the tracking portfolio two main objectives are employed: the tracking error and the excess return.

The tracking error (TE) is defined by the p-norm as:

$$TE = \frac{1}{T}\left\| r_t - R_t \right\|_p = \left(\sum_{t=1}^{T} \left| r_t - R_t \right|^p \right)^{\frac{1}{p}} \text{; p > 0,} \tag{5.7}$$

where r_t and R_t are the returns for the tracking portfolio and the index respectively. Portfolios' returns are adjusted for transaction costs when rebalancing occurs; 0.5% per transaction. For p = 2, the p-norm is equal to the Euclidean norm which represents the Root Mean Squared Error (RMSE) as expressed by the following equation:

$$TE = RMSE = \sqrt{\sum_{t=1}^{T} \left(r_t - R_t \right)^2 / T}. \tag{5.8}$$

The tracking error is measured with the RMSE criterion, which according to Beasley et al. (2003) is one of the most effective measurements for addressing this type of index tracking problems. Using only the variance of $\{(r_t - R_t) | t = 1,...,T\}$ as a tracking error measure (see Franks, 1992; Pope and Yadav, 1994; Connor and Leland, 1995; Buckley and Korn, 1998; Larsen and Resnick, 1998; Rohweder, 1998; Wang, 1999), could potentially lead to erroneous results, as the tracking portfolios would constantly underperform the index because they would ignore the bias proportion $(r_t - R_t)$. For example, let $M > 0$ be a constant, when $r_t = R_t - M \ \forall t$ the tracking portfolio has a zero tracking error, but will always underperform the benchmark index.

The mean Excess Return (ER) over that of the benchmark index is given by the following equation:

$$ER = \sum_{t=1}^{T} \left(r_t - R_t \right) / T. \tag{5.9}$$

Excess return gives a competitive advantage to any index fund that can historically show returns over and above the index, even at the cost of a higher degree of tracking error. It can be a measurement for distinguishing between competing funds besides the amount they charge for participation. The complete formulation of the objectives and constraints used to solve the index tracking problem is the following:

Minimize: $\lambda \times RMSE - (1-\lambda) \times ER$ (5.10)

Under the constraints: $\sum_{i=1}^{N} P_{iT} x_i = C$ (5.11)

$z_i \varepsilon C \le P_{iT} x_i \le z_i C \qquad \forall i = 1,...,N;\ \varepsilon \ge 0.05{*}\mathrm{C}$ (5.12)

$\sum_{i=1}^{N} z_i \le K$ (5.13)

$x_i \ge 0, \quad z_i \in \{0,1\} \quad \forall i = 1,...,N$

where λ $(0 \le \lambda \le 1)$ is the generalised minimization objective for the index tracking problem; a metric controlling for the trade-off between tracking error and excess return. In case λ = 1, the tracking portfolio has as its main objective to minimize the tracking error (pure index tracking), whereas when λ = 0, the portfolio's main goal is to maximize the excess return. The first constraint ensures that the value of the portfolio at the end of the in-sample period will be equal to the available capital to the investor, C. Using the rolling window method, the same rule applies for every rebalancing period. In addition, P_{iT} is the price of stock i at time T, whereas x_i is the weight of each stock that participates in the tracking portfolio. The last two constraints relate to the weights and total number of each participating stock in the portfolio; variable ε represents the minimum weight of each stock set at 5% of the available capital, and variable z is a decision variable which takes the value one (zero) when a stock is (is not) included in the basket. Finally it is assumed that all portfolios are long-only and also fully invested.

5.5. Empirical results

5.5.1. Tracking the Spot Energy Index

After developing an investable model for seeking returns comparable to the Spot Energy Index, the performance characteristics of the proposed strategy are examined. This section presents the empirical evidence on index tracking in the energy commodity markets using equity portfolios. The size of the five test problems ranges from N = 41 (UK Filter) to N = 97

(FTSE 100 Index); in the case of the Bovespa Composite N = 53, for the Dow Jones Composite Average N = 65, and for the US Filter N = 77. The stocks picked by both the DE and the GA from the aforementioned stock pools are used to track the performance of the SEI[34]. The initial capital of the investment portfolio is set equal to C = $100,000. Figures 5-1 and 5-2 show the convergence of both the DE and the GA during the in-sample period, of the Spot Energy Index with the Bovespa, DJIA, FTSE 100, UK Filter and US Filter baskets respectively. The case considered in the two graphs is for monthly rebalancing, with λ=0.6 and portfolios of maximum 15 stocks. In the empirical analysis, tracking portfolios consisting of maximum K stocks are used with K = 10, 15, and 20. This aligns with the findings of Chang et al. (2009) that investors should include in their tracking portfolios about one third of the total assets included in the search space, since those tracking portfolios that included more assets constantly underperformed. In another study, Maringer and Oyewumi (2007) show that including roughly 50% of the available assets is satisfactory enough to get the desirable properties in the tracking portfolios. Different attitudes corresponding to three different trade-offs between tracking error and excess return are also considered, with λ = 0.6, 0.8, and 1; thus, moving from maximising excess return to minimising tracking error. Then, the heuristic is repeated ten times with the same set of parameters per run, from which the best solution is chosen.

[34] All tracking portfolio strategies ran for both evolutionary algorithms were implemented with the Matlab 7.8.0 software on a PC with a processor T2600 at 2.16GHz and 2GB Ram. The average time for the completion of the training of the algorithm in-sample, along with the time needed for producing the output of the out-of-sample performance of each strategy is about 50 minutes. The computational time was very similar, with a variation of ±10%, not only across the different pools of stocks, but also between the DE and the GA.

Figure 5-1: DE convergence, during the in-sample period, of the Spot Energy Index with the Bovespa, DJIA, FTSE 100, UK Filter and US Filter baskets, respectively; λ=0.6, with maximum 15 stocks in the basket, rebalanced monthly.

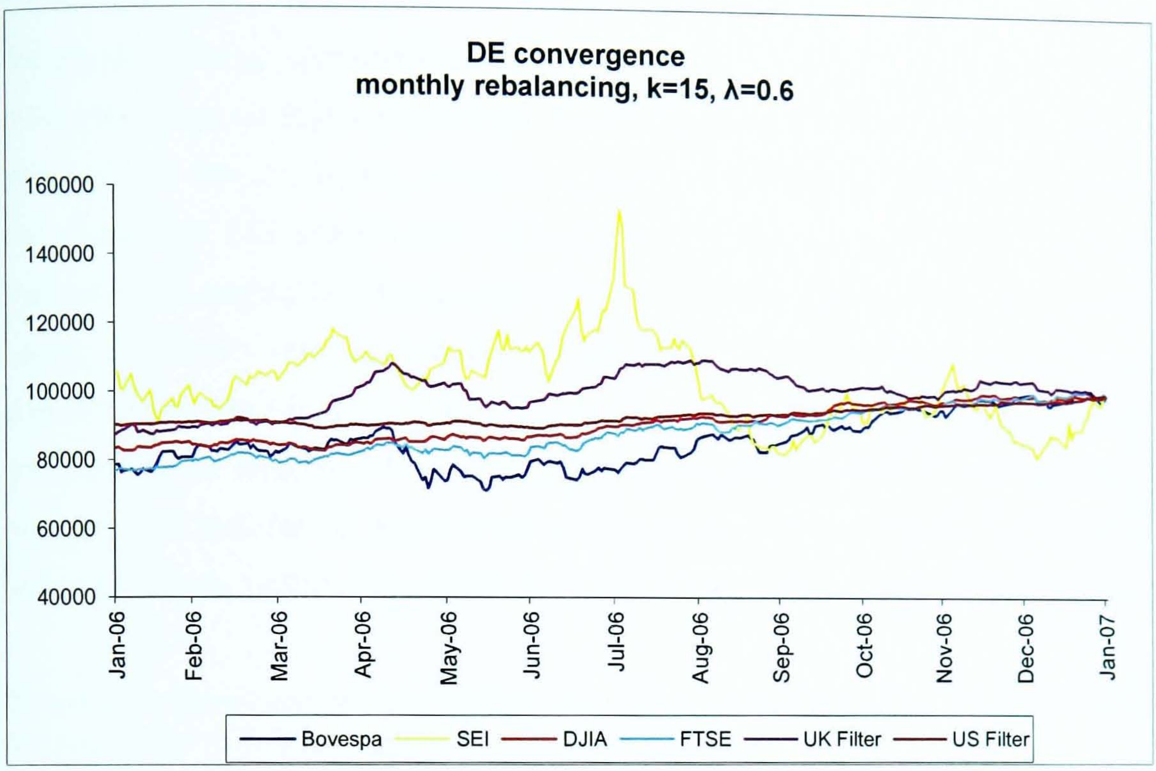


Figure 5-2: GA convergence, during the in-sample period, of the Spot Energy Index with the Bovespa, DJIA, FTSE 100, UK Filter and US Filter baskets, respectively; λ=0.6, with maximum 15 stocks in the basket, rebalanced monthly.

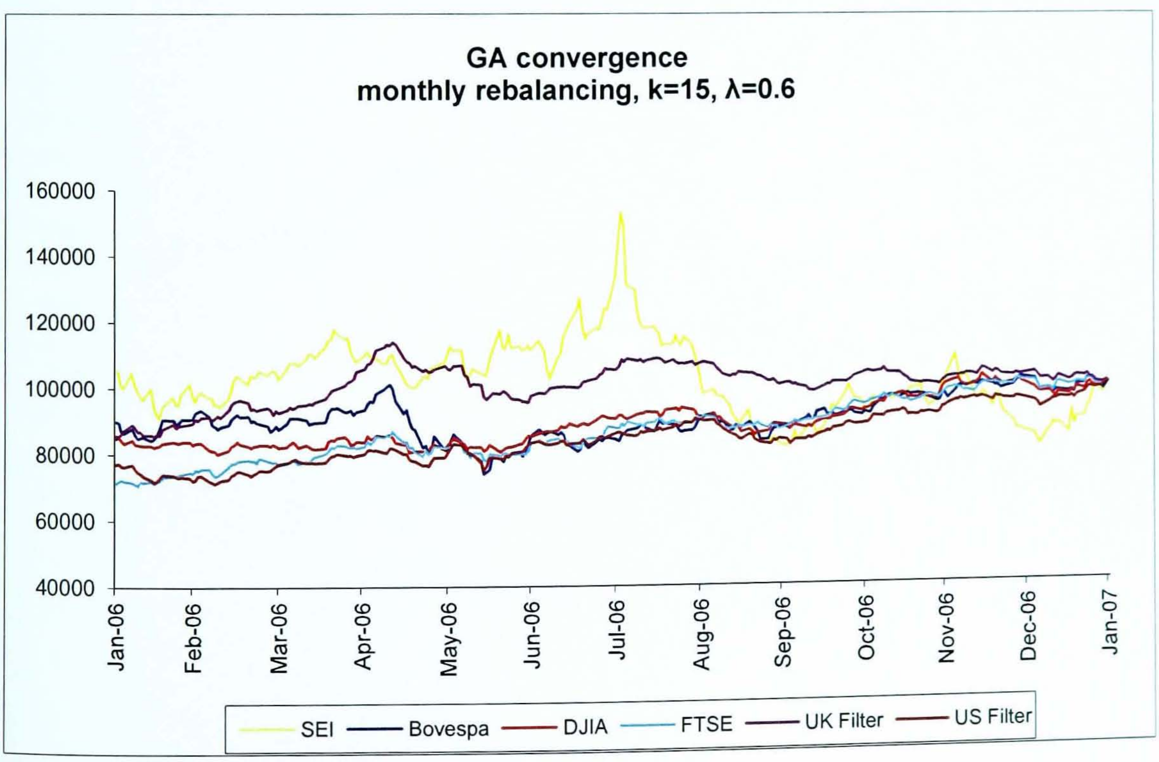
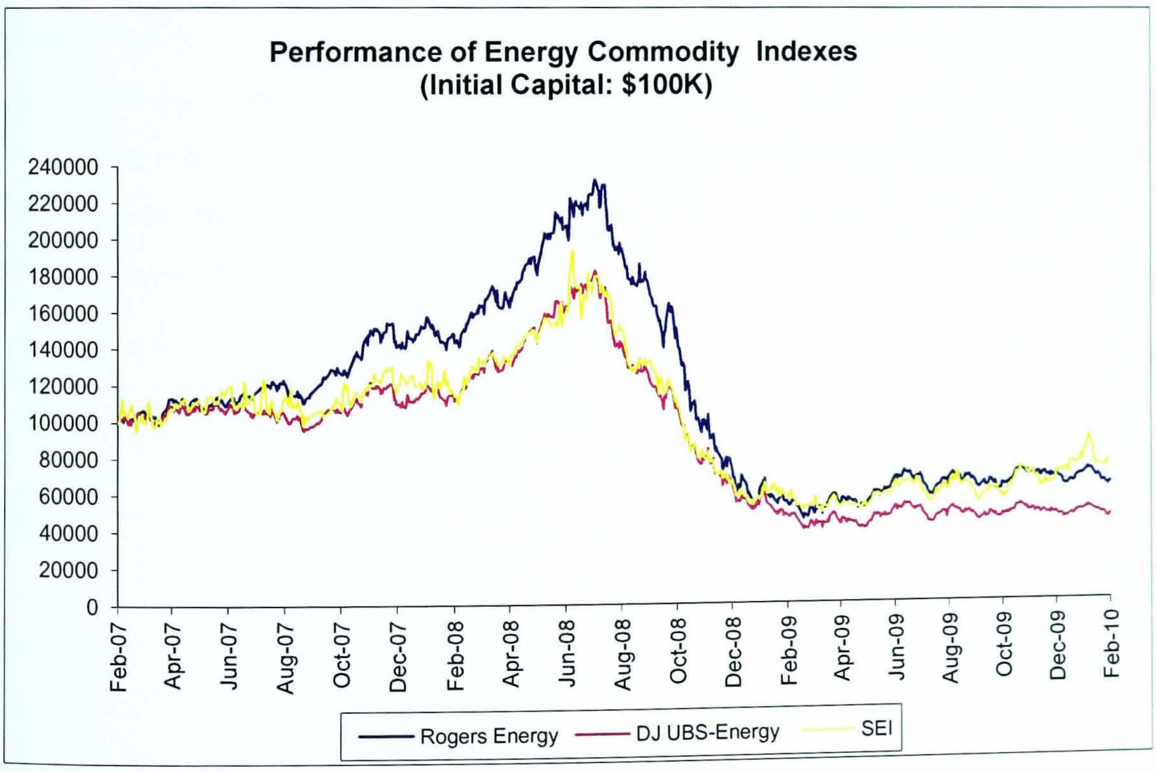


Figure 5-3 presents the performance of a $100K portfolio fully invested in three energy commodity indexes; the SEI, the Dow Jones-UBS Energy Index, and the Rogers Energy Commodity Index. The former represents the return available to the holder of the basket of the physical energy commodities comprising the SEI[35], and the latter total return indexes reflect the return on fully collateralized futures positions. The Dow Jones–UBS Energy Sub-Index and the Roger's Energy Commodity Index are selected for comparison reasons against the constructed SEI and the selected portfolios, as they are two of the most established indexes in the market; besides, the correlation between the energy sub-indexes of other well-known commodity indexes, such as the S&P GSCI, is extremely high. From figure 5-3 it is also observed that for most of the out-of-sample period, the SEI and Rogers Energy have performed better than the DJ UBS-Energy. However, especially during the last year, SEI has outperformed both futures based indexes. This confirms the fact that futures' based indexes underestimate the underlying commodity market price trends in relation to a spot index.

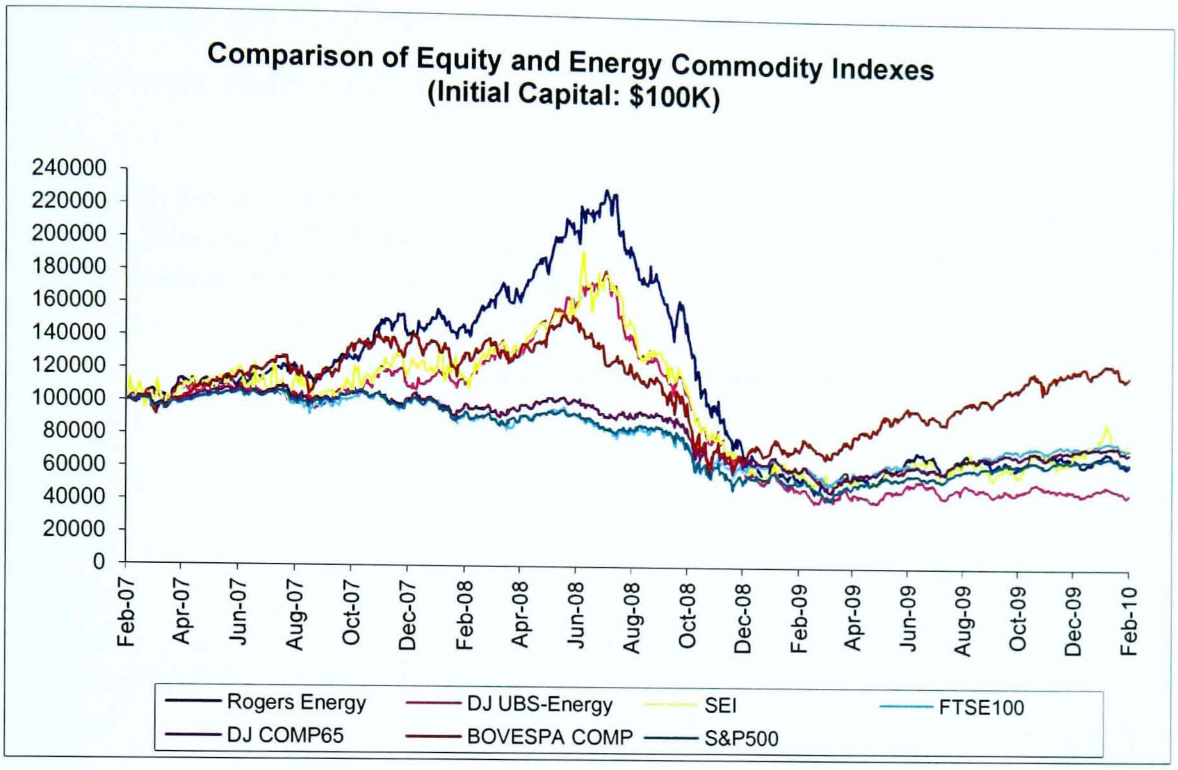
Figure 5-3: Three-year out-of-sample performance comparison of long-only portfolios invested in the SEI, Rogers Energy and DJ UBS Energy Indexes.



[35] The constructed Spot Energy Index tracks the evolution of the relevant commodities' spot prices setting an upper bound on the return available to an investor, since it ignores any costs associated with the holding of the physical commodities like storage, insurance etc.

Figure 5-4 shows the relative performance over the out-of-sample period of the three aforementioned commodity indexes next to four financial indexes, the S&P 500 Composite, the Dow Jones Composite Average, FTSE 100, and Bovespa Composite. When global markets entered the recent global economic recession towards the end of 2007, a big price correction in both equities and commodities markets followed. It is observed that energy commodities delivered higher returns for about one year, until the end of 2008, proving to be a better investment during the recession period. This finding aligns with Weiser (2003) who concludes that commodity futures, during the period of 1970-2003, perform well in the early stages of a recession when usually stocks tend to disappoint. Gorton and Rouwenhorst (2006), as well as Vrugt et al. (2004) also find that during late expansion and early recession periods of the business cycle, commodity returns are generally above their average, outperforming stocks and bonds that generally are below their average. The aforementioned prove that there is huge potential for various timing and index tracking strategies, as the one proposed in this thesis, to be applied to energy commodities markets and deliver superior returns to investors. From figure 5-4 it can also be seen that the indexes from the US and UK equity markets are not capable to follow the upward trend of energy commodities, except the Bovespa index that follows rather closely the high commodities' returns during the recession period, having a faster rebounding during the last year, outperforming all other equity and commodity indexes. This reflects the unique energy significance of Brazil to the global scene, and thus justifies the inclusion in this thesis of stocks from the Bovespa pool to track the performance of the SEI.

Figure 5-4: Three-year out-of-sample performance comparison of long-only portfolios invested in the three Energy Commodity Indexes, SEI, Rogers Energy and DJ UBS Energy, and in the four benchmark Stock Indexes, FTSE 100, S&P 500, DJ Comp65 and Bovespa Comp.



Next, figures 5-5 and 5-6 display the SEI against quarterly rebalanced portfolios selected from the DE and GA respectively. The portfolios consist of maximum 15 stocks and these are the FTSE 100, DJIA, Bovespa, UK Filter and US Filter, respectively; results are shown for $\lambda = 1$. Looking at the figures it is observed that during and towards the end of the recession period, the benchmark index can be better tracked with the Bovespa baskets followed by the UK Filter baskets; whereas during the last year it is the US Filter and DJIA baskets that perform better. The portfolios comprising of optimally selected energy related stocks can successfully track the SEI, generating similar returns for most of the out-of-sample period. This is in line with Hammoudeh et al. (2004) who conclude that WTI spot prices and their respective NYMEX future prices explain the stock price movement of oil related firms, with the spot and futures prices volatility having a volatility-echoing effect on the respective stock prices. However, there are contradictory views in the literature as Schneeweis and Spurgin (1997) conclude that direct stock and bond investment cannot provide consistent risk/ return attributes similar to various commodity and managed futures indexes. In this study, the US Filter and UK Filter results verify that when energy related stocks are selected, they can better replicate the risk and return trade-off of the SEI. The same applies for the Bovespa baskets since the Brazilian stock exchange has a large number of energy and commodity related listed companies that would closely follow any developments in the international energy markets. In addition, between the DE and GA selected portfolios, from the graphs it seems that the latter ones can follow more closely the performance of the SEI, achieving highest excess returns for the final out-of-sample year.

Figure 5-5: Out-of-sample tracking of the Spot Energy Index with the Bovespa, DJIA, FTSE 100, UK Filter and US Filter baskets, respectively; λ=0.8, with maximum 15 stocks in the basket, rebalanced quarterly using the DE.

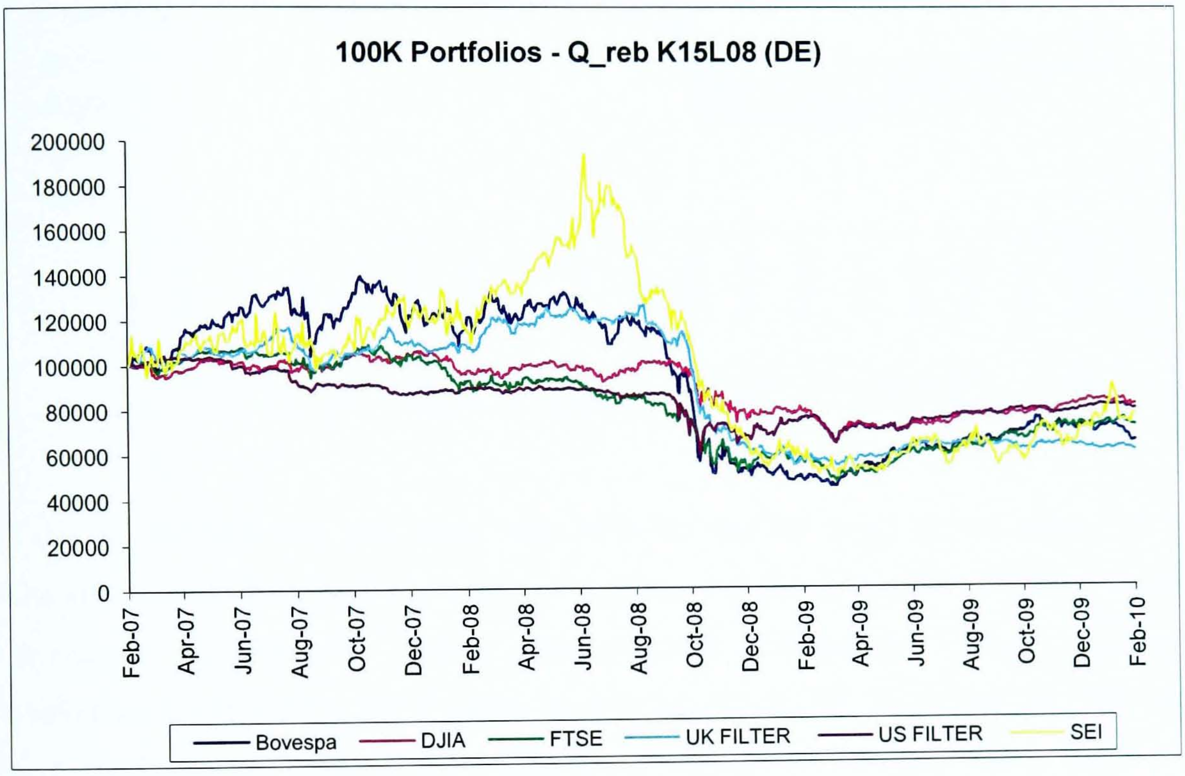


Figure 5-6: Out-of-sample tracking of the Spot Energy Index with the Bovespa, DJIA, FTSE 100, UK Filter and US Filter baskets, respectively; λ=0.8, with maximum 15 stocks in the basket, rebalanced quarterly using the GA.

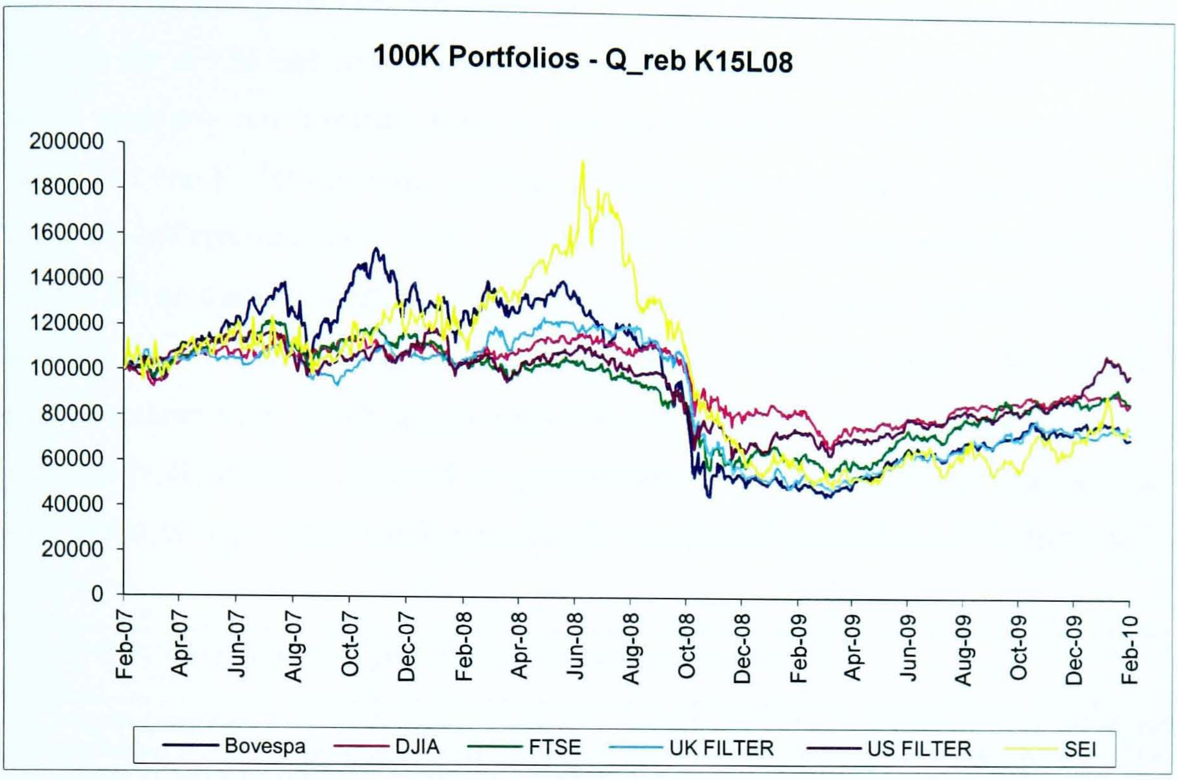


Table 5-2 presents the root mean squared errors and the mean excess returns of both the Genetic and Differential Evolution algorithms employed, under all three rebalancing strategies; buy-and-hold, monthly, and quarterly rebalancing. Using formal statistical evaluation criteria, the better tracking performance of the UK Filter and US Filter baskets is also confirmed. In terms of the competing portfolios' RMSEs, the DE is more consistent across the various portfolios, whereas the GA selects portfolios that exhibit larger differences between the worst and best performing ones. Additionally, in general GA tends to select portfolios that have a lower tracking error and thus track better the benchmark index when compared to the ones selected from the DE. Another interesting observation is that, although the RMSEs are improved when rebalancing occurs, increasing the frequency from quarterly to monthly has only a marginal effect. These results are more profound for the portfolios selected by the DE and align with Dunis and Ho (2005) who find that when comparing alternative rebalancing frequencies, a quarterly portfolio update is preferable to monthly, semi-annual or annual reallocations. In terms of their excess returns, in most cases, the portfolios selected by the GA tend to outperform the ones selected by the DE. The UK Filter and US Filter baskets, that also have the lowest tracking errors (see panels D and E), have excess returns that in some cases are positive, indicating that the selected portfolios, on average, over the out-of-sample period, over-perform the SEI. In the case of the US Filter baskets selected by the GA, the index is constantly outperformed in terms of excess returns (8.10% for K=20 and λ=0.6 under monthly rebalancing, and 6.14% for K=15 and λ=0.6 under quarterly rebalancing); there is only one exception for both rebalancing frequencies when λ=1 and K=10 where the portfolios under-perform the index. This is an indication that the trade-off criterion does work, and leads to portfolios that compromise any excess return over a better tracking performance as expressed by the smaller RMSEs. Thus, taking into account the fact that commodity indexes performed better compared to the financial indexes over the three-year out-of-sample period (except the Bovespa Composite, see figure 5-4), with the methodology employed the performance of the SEI is closely replicated, and in the case of the energy related stock portfolios the benchmark index is even outperformed.

Table 5-2: Index tracking performance of selected portfolios.

Our sample spans from February 15, 2006 to February 18, 2009. The first two years are used as the estimation period whereas the last year is our test period. The tracking portfolios are created based on the stocks that the Differential Evolution and Genetic Algorithms choose. To decide which stocks will be included in the tracking portfolio, we use two main objectives, the tracking error and the excess return. K is the maximum number of stocks allowed to be included in the selected baskets. λ is the generalised minimization objective for the index tracking problem; in the case that λ takes the value of 1, the tracking portfolio has as its main objective to minimize the tracking error, whereas, when λ equals 0 the portfolio's main goal is to maximize the excess return. Our tracking portfolios include stocks picked each time from the Dow, FTSE 100, Bovespa, UK Filter and US Filter stock pools which contain N = 65, 97, 53, 41, and 77 stocks, respectively. Panels A, B, C, D and E report the out-of-sample daily Root Mean Squared Errors (RMSE) and mean daily percentage (%) Excess Returns, as defined in equations (5.8) and (5.9), respectively. We also report the results for monthly and quarterly rebalancing. Under both rebalancing strategies the weights of the tracking portfolios are estimated based on the available data in the rolling window in-sample period (one year), every month and quarter, respectively. Portfolios' returns are adjusted for transaction costs of 0.5% for each transaction.

		No Rebalance				Monthly Rebalance				Quarterly Rebalance			
		RMSE		Mean ER (%)		RMSE		Mean ER (%)		RMSE		Mean ER (%)	
(K)	(λ)	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA
Panel A: Bovespa													
10	0.6	0.0346	0.0344	0.0136	0.0324	0.0331	0.0329	-0.0432	-0.0104	0.0333	0.0332	-0.0389	0.0134
	0.8	0.0343	0.0359	0.0176	0.0347	0.0330	0.0326	-0.0480	-0.0471	0.0332	0.0329	-0.0438	-0.0416
	1	0.0343	0.0362	0.0189	0.0133	0.0330	0.0327	-0.0545	-0.0689	0.0333	0.0332	-0.0472	-0.0236
15	0.6	0.0345	0.0359	0.0161	0.0239	0.0331	0.0327	-0.0427	-0.0063	0.0333	0.0332	-0.0411	-0.0148
	0.8	0.0343	0.0361	0.0181	0.0334	0.0330	0.0327	-0.0487	-0.0298	0.0332	0.0331	-0.0431	-0.0280
	1	0.0343	0.0356	0.0180	0.0238	0.0330	0.0327	-0.0533	-0.0418	0.0332	0.0333	-0.0442	-0.0312
20	0.6	0.0345	0.0354	0.0148	0.0233	0.0331	0.0331	-0.0436	0.0094	0.0333	0.0335	-0.0417	0.0209
	0.8	0.0343	0.0358	0.0186	0.0329	0.0330	0.0327	-0.0488	-0.0052	0.0332	0.0333	-0.0427	0.0000
	1	0.0343	0.0357	0.0164	0.0284	0.0330	0.0328	-0.0541	-0.0346	0.0333	0.0334	-0.0461	-0.0210
Panel B: DJIA													
10	0.6	0.0319	0.0328	-0.0232	-0.0257	0.0318	0.0315	-0.0479	-0.0115	0.0319	0.0319	-0.0302	-0.0243
	0.8	0.0319	0.0330	-0.0238	-0.0210	0.0318	0.0316	-0.0511	-0.0312	0.0318	0.0318	-0.0323	-0.0273
	1	0.0319	0.0330	-0.0249	-0.0218	0.0318	0.0313	-0.0522	-0.0274	0.0319	0.0317	-0.0314	-0.0172
15	0.6	0.0320	0.0329	-0.0244	-0.0200	0.0319	0.0315	-0.0503	-0.0332	0.0319	0.0318	-0.0297	-0.0172

	0.8	0.0319	0.0330	-0.0240	-0.0250	0.0318	0.0314	-0.0515	-0.0244	0.0319	0.0319	-0.0311	-0.0192
	1	0.0319	0.0328	-0.0246	-0.0239	0.0318	0.0313	-0.0515	-0.0410	0.0319	0.0319	-0.0314	-0.0283
20	0.6	0.0319	0.0328	-0.0228	-0.0251	0.0319	0.0315	-0.0514	-0.0239	0.0319	0.0319	-0.0313	-0.0005
	0.8	0.0319	0.0329	-0.0235	-0.0289	0.0318	0.0315	-0.0529	-0.0300	0.0319	0.0318	-0.0301	-0.0332
	1	0.0319	0.0328	-0.0253	-0.0323	0.0318	0.0313	-0.0505	-0.0344	0.0319	0.0317	-0.0308	-0.0051
Panel C: FTSE 100													
10	0.6	0.0315	0.0318	-0.0450	-0.0359	0.0309	0.0299	-0.0597	-0.0260	0.0308	0.0303	-0.0438	0.0106
	0.8	0.0317	0.0316	-0.0469	-0.0246	0.0309	0.0302	-0.0701	-0.0416	0.0309	0.0305	-0.0475	-0.0255
	1	0.0316	0.0314	-0.0495	-0.0193	0.0310	0.0300	-0.0735	-0.0635	0.0310	0.0307	-0.0461	-0.0334
15	0.6	0.0315	0.0318	-0.0512	-0.0253	0.0309	0.0303	-0.0674	-0.0327	0.0308	0.0303	-0.0468	-0.0180
	0.8	0.0316	0.0313	-0.0477	-0.0220	0.0309	0.0302	-0.0634	-0.0449	0.0309	0.0306	-0.0416	-0.0127
	1	0.0316	0.0312	-0.0490	-0.0175	0.0310	0.0303	-0.0699	-0.0682	0.0310	0.0306	-0.0456	-0.0349
20	0.6	0.0315	0.0317	-0.0507	-0.0271	0.0309	0.0303	-0.0705	-0.0311	0.0308	0.0305	-0.0442	-0.0092
	0.8	0.0316	0.0313	-0.0484	-0.0297	0.0310	0.0303	-0.0681	-0.0656	0.0309	0.0305	-0.0445	-0.0145
	1	0.0316	0.0313	-0.0492	-0.0245	0.0310	0.0301	-0.0679	-0.0600	0.0310	0.0306	-0.0449	-0.0208
Panel D: UK Filter													
10	0.6	0.0318	0.0309	-0.0900	-0.0834	0.0299	0.0294	-0.0712	0.0019	0.0300	0.0296	-0.0681	-0.0032
	0.8	0.0315	0.0312	-0.0818	-0.0834	0.0300	0.0290	-0.0680	-0.0725	0.0301	0.0296	-0.0611	-0.0412
	1	0.0317	0.0307	-0.0809	-0.0751	0.0300	0.0292	-0.0713	-0.1371	0.0301	0.0297	-0.0632	-0.1049
15	0.6	0.0312	0.0309	-0.0825	-0.0519	0.0299	0.0294	-0.0782	-0.0427	0.0300	0.0298	-0.0711	-0.0341
	0.8	0.0313	0.0309	-0.0847	-0.0408	0.0300	0.0293	-0.0720	-0.0501	0.0300	0.0296	-0.0707	-0.0410
	1	0.0313	0.0308	-0.0846	-0.0531	0.0300	0.0293	-0.0782	-0.1083	0.0301	0.0297	-0.0601	-0.0459
20	0.6	0.0311	0.0305	-0.0796	-0.0586	0.0299	0.0297	-0.0764	-0.0508	0.0300	0.0299	-0.0717	-0.0446
	0.8	0.0311	0.0303	-0.0858	-0.0451	0.0299	0.0294	-0.0752	-0.0790	0.0300	0.0298	-0.0697	-0.0391
	1	0.0311	0.0304	-0.0763	-0.0516	0.0300	0.0295	-0.0747	-0.0794	0.0301	0.0296	-0.0676	-0.0494
Panel E: US Filter													
10	0.6	0.0307	0.0329	-0.0258	-0.0442	0.0306	0.0297	-0.0449	0.0710	0.0309	0.0307	-0.0364	0.0249
	0.8	0.0308	0.0321	-0.0265	-0.0780	0.0309	0.0295	-0.0603	0.0607	0.0310	0.0300	-0.0345	0.0240
	1	0.0309	0.0318	-0.0234	-0.0314	0.0310	0.0294	-0.0688	-0.0278	0.0310	0.0298	-0.0367	-0.0172
15	0.6	0.0307	0.0321	-0.0246	-0.0581	0.0309	0.0306	-0.0497	0.1241	0.0310	0.0308	-0.0322	0.0614
	0.8	0.0308	0.0327	-0.0244	-0.0511	0.0309	0.0296	-0.0575	0.0212	0.0310	0.0301	-0.0336	0.0016
	1	0.0308	0.0322	-0.0254	-0.0566	0.0309	0.0295	-0.0648	-0.0027	0.0310	0.0302	-0.0342	0.0204
20	0.6	0.0307	0.0327	-0.0261	-0.0668	0.0309	0.0301	-0.0510	0.0810	0.0310	0.0308	-0.0274	0.0345
	0.8	0.0308	0.0319	-0.0251	-0.0320	0.0309	0.0296	-0.0603	0.0210	0.0310	0.0303	-0.0329	0.0369
	1	0.0307	0.0311	-0.0226	-0.0649	0.0309	0.0294	-0.0662	0.0071	0.0310	0.0301	-0.0352	0.0126

Now in terms of the risk/ return trade-off (λ), it is observed that results are very similar between portfolios where λ=0.8 and 1. In most cases, the risk/ return trade-off criterion tends to perform well, selecting portfolios with higher returns and also relatively higher RMSEs. Moreover, the portfolios selected by the GA tend to be more consistent when the risk/ return trade-off rule is applied, compared to the ones selected by the DE. Overall, when considering both the tracking performance and the excess returns of the various portfolios, those with λ=0.8 should be preferred. As far as the maximum number of stocks criterion is concerned, in all three rebalancing scenarios, portfolios with K=10 tend to perform worst in terms of RMSEs but they do slightly better in terms of excess returns, for both the DE and GA selected portfolios. This is also an indication that the more stocks are included in the portfolio, the higher the transaction costs when a rebalancing occurs. Overall, it is suggested that portfolios with a maximum of 15 stocks should be selected, as there still seems to be a valuable compensation for the additional information and diversification when rebalancing, against the extra rebalancing costs.

According to the results, for both algorithms, monthly rebalancing is overall the best option in terms of RMSEs, closely followed by quarterly rebalancing; whereas when looking at excess returns, quarterly rebalancing appears to improve portfolio performance. This last observation can be confirmed by figures 5-8 and 5-10 where the UK Filter baskets selected by the DE and GA, respectively, are plotted, with K=20 and λ=1, for all three rebalancing frequencies. Also, from figures 5-7 and 5-9 it is clearly seen that for the Bovespa baskets, the buy-and-hold strategy performs better than both the quarterly and monthly rebalancing. The return of a buy and hold portfolio may be higher than that of a rebalanced portfolio when transaction costs are considered, but it is important to determine the source of the higher return; whether it is greater capital efficiency as expressed by a higher Sharp or Information ratio, or greater risk. Plaxco and Arnott (2002) showed that rebalanced portfolios typically have higher Sharpe ratios than buy-and-hold portfolios; a finding that suggests that the possible outperformance of a buy-and-hold portfolio may be the result of greater risk. Results are more apparent for the GA portfolios, as for the DE portfolios the difference between monthly and quarterly rebalancing is only marginal. In the case of the UK Filter basket, picked by the GA, there is an obvious difference in performance when rebalancing quarterly, against a monthly rebalancing. A more in depth analysis comparing the portfolios' information ratios is presented in the following section. On average, based on the results from table 5-2, K=15 and λ=0.8 is the most desirable combination providing the best results for most tracking portfolios. Although it is up to the investors' risk/ return appetite to decide whether rebalancing their portfolio quarterly, which comes with an extra cost, it is better than no rebalancing at all. The same applies and as to whether λ=0.8 should be used compared to a more risky trade-off when λ=0.6.

Figure 5-7: Out-of-sample performance of the Bovespa portfolio; λ=1, with maximum 20 stocks in the basket, under the three rebalancing frequencies as selected by the DE.

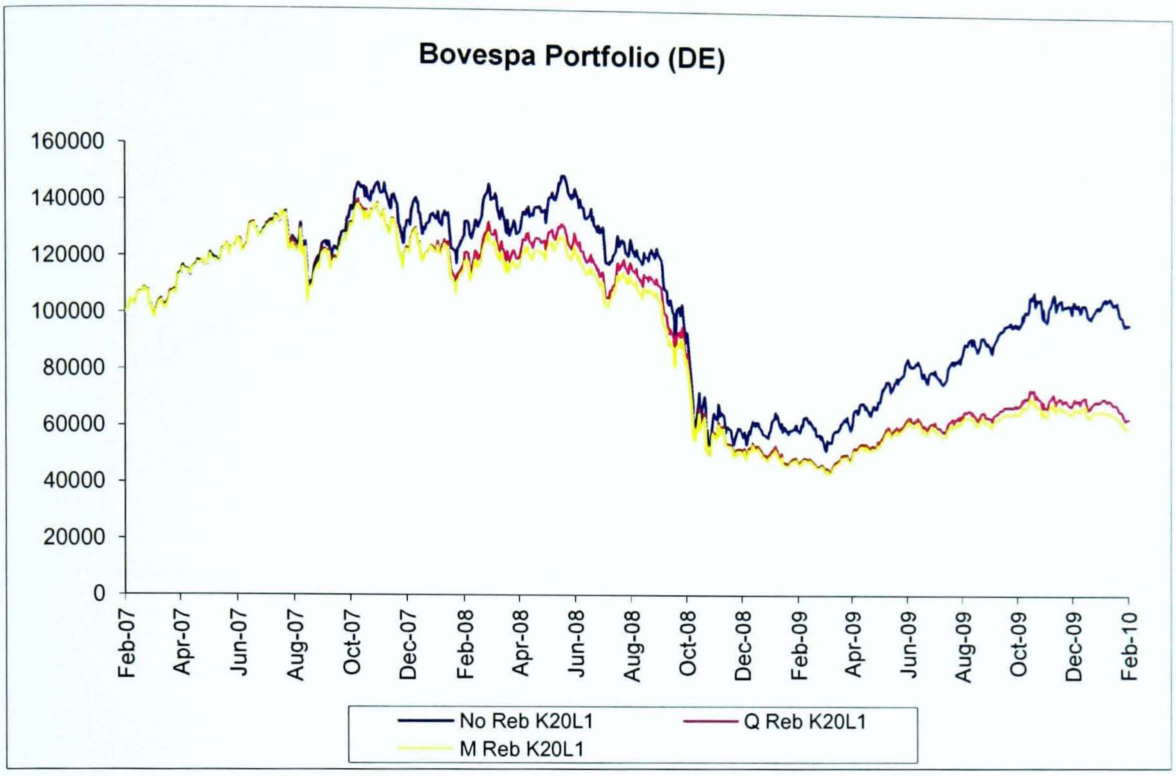


Figure 5-8: Out-of-sample performance of the UK Filter portfolio; λ=1, with maximum 20 stocks in the basket, under the three rebalancing frequencies as selected by the DE.

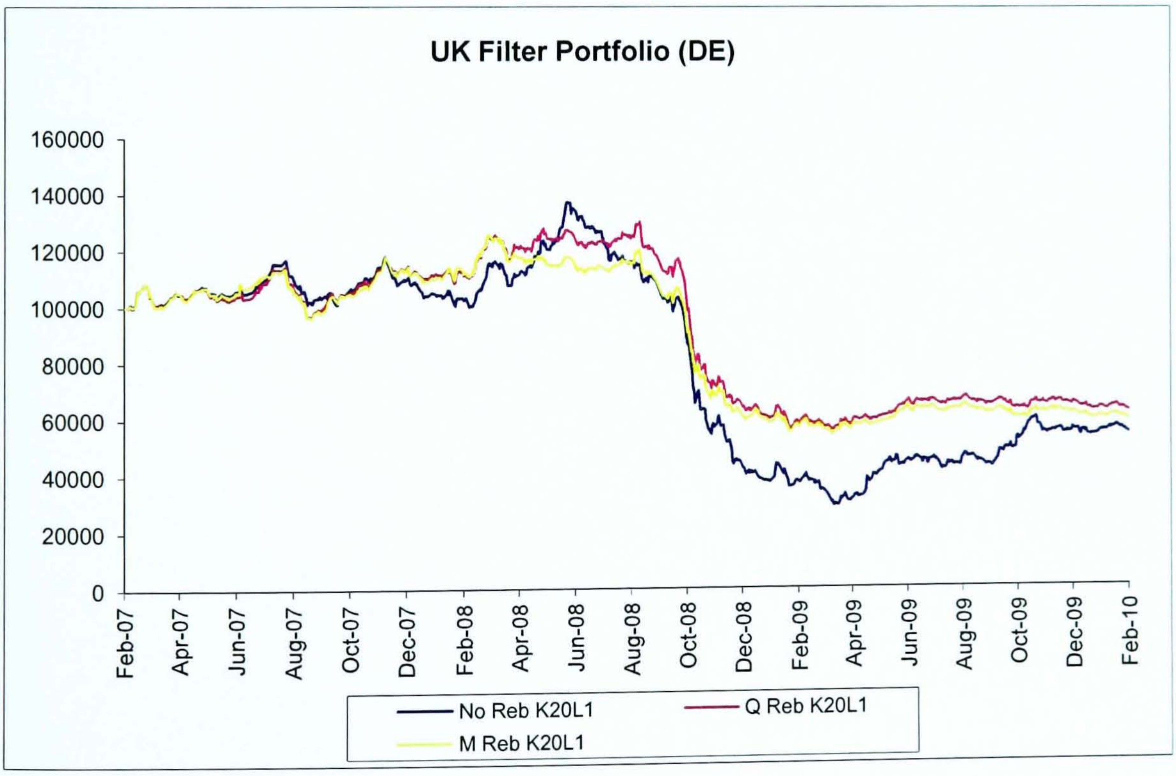


Figure 5-9: Out-of-sample performance of the Bovespa portfolio; $\lambda=1$, with maximum 20 stocks in the basket, under the three rebalancing frequencies as selected by the GA.

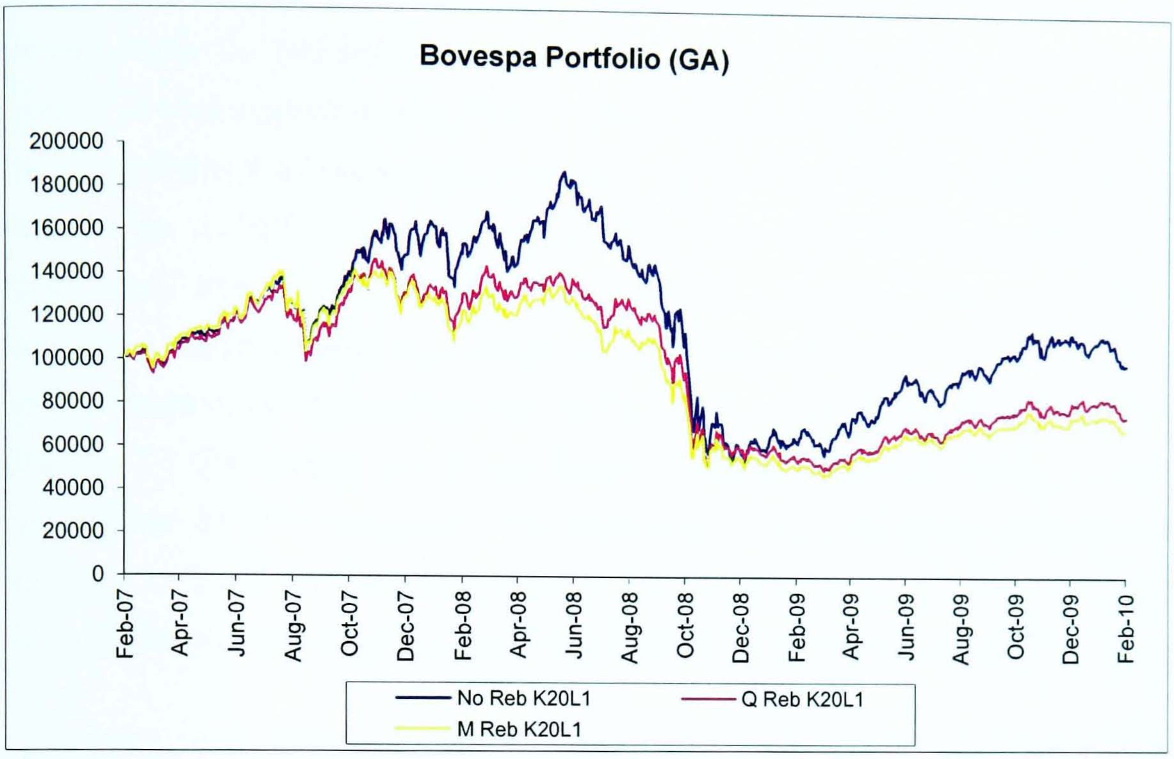
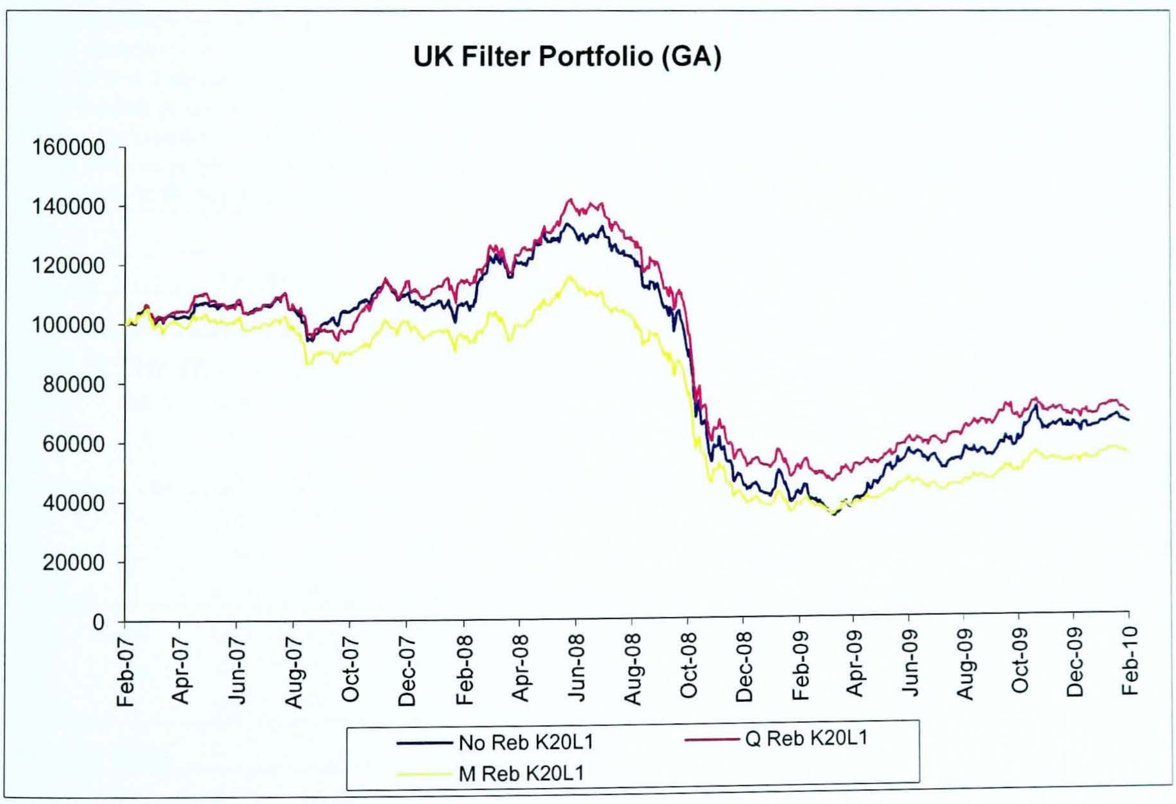


Figure 5-10: Out-of-sample performance of the UK Filter portfolio; $\lambda=1$, with maximum 20 stocks in the basket, under the three rebalancing frequencies as selected by the GA.



5.5.2. Statistical properties of selected portfolios

Tables 5-3, 5-4 and 5-5 present some distributional statistics of the selected portfolios' returns under the buy-and-hold, monthly and quarterly rebalancing respectively. Also, in panel F of each aforementioned table, the statistics and relevant performance measures for the following indexes are reported for comparison reasons: two Total Return Energy Commodity Indexes, the DJ UBS-Energy and Rogers Energy Commodity, the three stock indexes used to draw stocks from to construct the tracking portfolios, Bovespa, DJIA and FTSE 100, and finally the most commonly used benchmark in the finance industry, the S&P 500. According to the historical annualised volatilities for the out-of-sample period, the SEI is more volatile than the DJ UBS-Energy and Rogers Energy Commodity Indexes; 48.40% as compared to 36.21% and 41.11% respectively. The respective volatility of the equity indexes is in the range of 27% to 38%. However, when comparing the information ratios, only the Bovespa index is able to generate a better risk-return performance compared to the SEI.

Table 5-3: Distributional statistics of portfolios' daily returns.

This table presents the annualised returns and volatilities of the tracking portfolios, the skewness and kurtosis, the correlation coefficient between the returns of the benchmark index and the portfolio that is used each time to replicate this benchmark, and the Information Ratio, under the No Rebalancing strategy. The Information Ratio (IR) is the ratio of each portfolio's return above the return of the benchmark index to the volatility of those returns. It measures the ability of the portfolio to generate excess returns relative to the benchmark index, and at the same time suggests consistency of performance. The IR can be expressed as the following ratio: IR = (Mean Excess Return of the Portfolio) / (Excess Returns' Volatility). Panels A, B, C, D and E represent the portfolios that include stocks picked each time from the Dow, FTSE 100, Bovespa, UK Filter and US Filter stock pools. Panel F presents, for comparison reasons, the relevant performance measures for two Total Return Energy Commodity Indexes, the DJ UBS-Energy and Rogers Energy Commodity, for the three stock indexes used to draw stocks from in order to construct the tracking portfolios, Bovespa, DJIA and FTSE 100, and finally the most commonly used benchmark in the finance industry, the S&P 500.

		No Rebalancing											
		An. Ret (%)		An. Vol. (%)		Skewness		Ex. Kurtosis		Correl. (%)		Info Ratio	
(K)	(λ)	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA
Panel A: Bovespa													
10	0.6	6.44	11.16	40.16	41.03	-0.282	-0.389	7.582	6.609	24.19	26.22	0.062	0.149
	0.8	7.44	11.76	39.22	45.37	-0.316	-0.325	7.813	5.933	24.01	26.19	0.081	0.153
	1	7.76	6.37	39.34	47.10	-0.320	-0.304	7.658	4.825	24.17	27.68	0.087	0.059
15	0.6	7.06	9.03	39.85	44.92	-0.272	-0.299	7.748	6.313	23.89	25.48	0.074	0.106
	0.8	7.56	11.42	39.27	47.02	-0.311	-0.359	7.732	4.550	23.95	27.63	0.083	0.147
	1	7.55	9.00	39.46	45.61	-0.327	-0.374	7.560	5.105	24.25	27.70	0.083	0.106
20	0.6	6.73	8.86	39.96	44.26	-0.275	-0.260	7.633	5.512	24.10	26.69	0.068	0.104
	0.8	7.68	11.29	39.54	45.01	-0.307	-0.350	7.608	5.942	24.40	26.04	0.086	0.146
	1	7.14	10.16	39.72	45.09	-0.324	-0.337	7.389	5.609	24.74	26.69	0.076	0.126
Panel B: DJIA													
10	0.6	-2.85	-3.46	22.18	31.14	0.571	0.406	11.674	11.823	12.33	19.84	-0.116	-0.124
	0.8	-2.98	-2.28	21.50	32.93	0.490	0.390	11.175	11.229	11.55	21.07	-0.118	-0.101
	1	-3.28	-2.48	21.44	31.48	0.366	0.547	10.852	12.525	11.10	19.31	-0.124	-0.105
15	0.6	-3.14	-2.03	22.69	31.68	0.563	0.546	12.006	12.512	12.66	19.97	-0.121	-0.096

	0.8	-3.05	-3.31	22.02	32.20	0.489	0.240	11.446	10.909	12.04	20.23	-0.119	-0.120
	1	-3.20	-3.01	21.86	32.17	0.426	0.394	10.942	11.654	11.76	21.26	-0.122	-0.115
20	0.6	-2.73	-3.33	22.55	32.03	0.515	0.220	11.418	10.750	12.83	20.96	-0.113	-0.122
	0.8	-2.91	-4.27	22.18	32.85	0.463	0.130	10.919	10.488	12.18	21.96	-0.117	-0.139
	1	-3.38	-5.13	21.65	31.66	0.403	0.250	10.538	10.939	11.57	20.61	-0.126	-0.156
Panel C: FTSE 100													
10	0.6	-8.34	-6.04	28.22	31.64	-0.059	-0.231	6.344	6.944	23.50	25.81	-0.227	-0.179
	0.8	-8.82	-3.18	28.84	30.89	-0.080	0.013	6.418	7.273	23.06	25.95	-0.235	-0.123
	1	-9.47	-1.87	29.44	30.66	-0.104	0.021	5.995	7.300	23.98	27.03	-0.248	-0.098
15	0.6	-9.90	-3.37	28.64	30.53	-0.110	-0.108	6.347	6.971	24.03	24.67	-0.258	-0.126
	0.8	-9.01	-2.54	28.99	30.12	-0.077	-0.044	6.360	7.176	23.51	26.91	-0.239	-0.112
	1	-9.33	-1.41	29.16	30.44	-0.080	0.041	6.207	6.916	23.71	27.35	-0.246	-0.089
20	0.6	-9.76	-3.83	28.49	30.41	-0.091	-0.183	6.393	6.922	23.82	24.94	-0.256	-0.136
	0.8	-9.20	-4.48	28.84	32.12	-0.063	0.021	6.499	6.589	23.75	29.06	-0.244	-0.151
	1	-9.38	-3.18	29.11	32.57	-0.080	-0.001	6.133	6.136	23.78	29.67	-0.247	-0.125
Panel D: UK Filter													
10	0.6	-19.68	-18.02	30.55	29.32	-0.006	-0.250	10.129	5.788	24.55	28.13	-0.449	-0.429
	0.8	-17.60	-18.01	29.29	30.23	-0.109	-0.114	9.151	5.918	24.65	27.38	-0.412	-0.424
	1	-17.37	-15.93	29.84	29.62	0.020	-0.404	10.024	4.821	24.47	29.50	-0.405	-0.389
15	0.6	-17.78	-10.08	29.25	31.89	-0.336	-0.712	7.537	4.866	26.08	30.75	-0.419	-0.266
	0.8	-18.35	-7.27	29.06	31.87	-0.241	-0.628	8.014	5.012	25.46	30.85	-0.430	-0.209
	1	-18.31	-10.37	29.00	30.59	-0.235	-0.658	8.539	4.740	25.51	29.82	-0.429	-0.273
20	0.6	-17.05	-11.75	28.76	30.28	-0.361	-0.703	7.774	4.804	26.08	30.94	-0.406	-0.304
	0.8	-18.61	-8.36	28.68	28.51	-0.323	-0.723	7.597	4.314	26.13	30.49	-0.438	-0.236
	1	-16.23	-9.99	28.20	28.48	-0.362	-0.808	7.526	5.115	25.88	29.77	-0.390	-0.269
Panel E: US Filter													
10	0.6	-3.49	-8.14	18.71	36.75	0.378	-0.125	16.744	7.485	17.50	27.28	-0.133	-0.213
	0.8	-3.68	-16.65	18.87	30.59	0.487	-0.031	19.319	6.308	16.69	22.75	-0.137	-0.385
	1	-2.89	-4.91	18.82	31.54	0.344	0.182	19.821	11.993	16.14	25.83	-0.120	-0.157
15	0.6	-3.21	-11.63	18.93	32.85	0.531	0.528	18.389	16.749	17.68	25.64	-0.127	-0.287
	0.8	-3.14	-9.86	18.98	35.24	0.467	0.240	20.067	12.534	16.81	26.05	-0.126	-0.248
	1	-3.39	-11.26	18.96	34.46	0.617	-0.104	21.177	8.574	17.00	27.26	-0.131	-0.279
20	0.6	-3.56	-13.83	19.05	33.98	0.526	0.374	17.797	15.279	17.95	24.28	-0.135	-0.324
	0.8	-3.32	-5.06	19.06	33.69	0.611	-0.091	20.461	7.872	16.95	27.94	-0.129	-0.159
	1	-2.69	-13.35	18.98	26.94	0.474	-0.361	21.563	9.317	17.35	24.35	-0.117	-0.332

Panel F: Indexes	**An.Ret. (%)**	**An.Vol. (%)**	**Skewn.**	**Ex. Kurt.**	**Correl. (%)**	**Info Ratio**
SEI	3.01	48.40	0.094	2.283	-	-
Bovespa	13.21	38.04	0.026	4.875	20.09	0.185
DJIA	-7.07	28.03	-0.053	4.636	12.90	-0.191
FTSE 100	-6.01	27.42	-0.009	5.374	24.34	-0.182
S&P500	-9.46	30.07	-0.162	5.999	14.51	-0.235
DJ UBS Energy-TR	-18.94	36.21	-0.166	1.102	43.83	-0.477
Rogers Energy Commodity-TR	-6.15	41.11	-0.189	2.099	44.02	-0.192

Table 5-4: Distributional statistics of portfolios' daily returns.

For further details, see notes in previous table.

		Monthly Rebalancing											
		An. Ret (%)		An. Vol. (%)		Skewness		Ex. Kurtosis		Correl.		Info Ratio	
(K)	(λ)	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA
Panel A: Bovespa													
10	0.6	-7.88	0.39	35.05	37.73	-0.685	-0.618	7.390	5.738	23.75	28.52	-0.207	-0.050
	0.8	-9.09	-8.87	34.67	36.78	-0.670	-0.653	7.242	6.686	23.79	28.43	-0.231	-0.229
	1	-10.74	-14.35	34.77	36.32	-0.651	-0.648	7.485	6.393	23.86	27.61	-0.262	-0.335
15	0.6	-7.77	1.41	35.05	37.50	-0.693	-0.384	7.545	6.491	23.76	29.05	-0.205	-0.031
	0.8	-9.27	-4.51	34.81	36.94	-0.667	-0.571	7.549	7.385	23.80	28.40	-0.234	-0.145
	1	-10.42	-7.52	34.78	36.19	-0.634	-0.405	7.463	7.580	23.87	27.44	-0.256	-0.203
20	0.6	-7.99	5.39	35.04	37.63	-0.689	-0.646	7.536	6.739	23.71	27.51	-0.209	0.045
	0.8	-9.30	1.69	34.81	36.13	-0.657	-0.598	7.467	5.913	23.79	27.05	-0.235	-0.025
	1	-10.62	-5.71	34.77	36.57	-0.647	-0.520	7.503	7.536	23.77	27.23	-0.260	-0.167
Panel B: DJIA													
10	0.6	-9.06	0.10	19.45	22.79	0.572	0.165	12.589	7.598	8.91	16.14	-0.239	-0.058
	0.8	-9.88	-4.85	19.62	22.96	0.554	0.422	13.159	10.442	9.21	15.63	-0.255	-0.156
	1	-10.14	-3.89	19.63	23.24	0.562	0.424	13.418	10.173	9.08	18.05	-0.260	-0.139
15	0.6	-9.68	-5.37	19.63	21.72	0.546	0.304	12.686	7.835	8.80	15.10	-0.251	-0.168
	0.8	-9.98	-3.15	19.61	22.41	0.573	0.270	13.150	8.099	9.17	16.58	-0.257	-0.123
	1	-9.96	-7.32	19.61	23.45	0.576	0.571	13.430	12.986	9.11	18.53	-0.257	-0.208
20	0.6	-9.96	-3.02	19.57	23.26	0.577	0.386	12.735	9.342	8.75	16.62	-0.256	-0.120
	0.8	-10.32	-4.56	19.63	22.81	0.567	0.174	13.190	8.242	8.93	16.41	-0.264	-0.151
	1	-9.73	-5.66	19.51	22.86	0.577	0.358	13.330	9.564	9.01	17.53	-0.252	-0.174
Panel C: FTSE 100													
10	0.6	-12.05	-3.54	26.26	28.79	0.005	0.008	6.062	8.298	24.46	32.96	-0.307	-0.138
	0.8	-14.67	-7.47	26.39	29.71	-0.016	0.097	5.871	6.692	24.45	32.29	-0.360	-0.219
	1	-15.51	-13.00	26.15	29.76	-0.029	0.100	5.730	8.650	24.13	33.24	-0.377	-0.336
15	0.6	-13.99	-5.23	26.23	29.08	-0.002	-0.179	6.251	6.001	24.45	30.85	-0.346	-0.171
	0.8	-12.96	-8.31	26.04	29.65	-0.080	0.059	6.050	8.000	24.08	32.12	-0.325	-0.236
	1	-14.61	-14.17	26.38	29.44	-0.058	-0.223	6.116	6.708	23.85	31.60	-0.357	-0.357
20	0.6	-14.77	-4.84	26.26	29.22	0.002	-0.311	6.298	6.610	24.27	31.24	-0.362	-0.163
	0.8	-14.16	-13.54	26.35	29.42	-0.011	-0.002	6.168	7.674	24.05	31.29	-0.349	-0.344
	1	-14.10	-12.11	26.43	29.22	0.019	0.015	6.227	6.851	23.96	32.02	-0.347	-0.316
Panel D: UK Filter													
10	0.6	-14.94	3.47	17.80	23.13	-1.134	-0.707	6.977	4.513	23.12	31.42	-0.377	0.010
	0.8	-14.14	-15.26	17.61	22.86	-1.060	-1.535	6.811	9.672	22.44	33.72	-0.360	-0.397
	1	-14.97	-31.53	17.68	23.42	-1.050	-0.925	6.879	5.862	22.50	33.09	-0.377	-0.746
15	0.6	-16.70	-7.75	17.72	23.56	-1.175	-0.839	7.074	4.375	23.16	31.61	-0.415	-0.231
	0.8	-15.13	-9.62	17.72	23.55	-1.145	-0.929	7.070	5.514	22.89	32.41	-0.381	-0.272
	1	-16.69	-24.28	17.69	23.71	-1.112	-1.054	6.971	6.130	22.79	32.60	-0.414	-0.587
20	0.6	-16.25	-9.78	17.71	24.10	-1.167	-0.912	6.890	4.482	23.02	30.10	-0.405	-0.271
	0.8	-15.94	-16.90	17.67	24.16	-1.140	-0.819	6.983	4.836	22.99	32.15	-0.398	-0.427
	1	-15.83	-16.99	17.64	24.40	-1.105	-0.867	6.832	5.252	22.65	31.68	-0.395	-0.427
Panel E: US Filter													
10	0.6	-8.31	20.89	19.22	26.62	-0.755	-0.140	19.511	10.044	18.65	31.80	-0.233	0.379
	0.8	-12.19	18.31	20.26	25.75	-0.742	-0.373	24.991	11.898	17.41	32.28	-0.309	0.326
	1	-14.33	-4.00	20.48	24.96	-0.954	-0.260	26.671	11.698	16.91	32.58	-0.352	-0.150

15	0.6	-9.52	34.28	20.19	27.25	-0.831	0.012	25.504	10.244	17.46	27.74	-0.255	0.645
	0.8	-11.48	8.34	20.25	26.54	-0.773	-0.118	24.625	16.027	17.59	32.31	-0.295	0.113
	1	-13.33	2.33	20.17	26.56	-0.870	-0.170	25.108	12.796	17.60	33.33	-0.333	-0.014
20	0.6	-9.84	23.41	20.28	27.26	-0.859	-0.280	25.937	7.271	17.37	30.34	-0.262	0.427
	0.8	-12.20	8.29	20.19	25.34	-0.853	0.180	24.818	9.723	17.25	31.49	-0.310	0.112
	1	-13.67	4.81	20.32	25.50	-0.836	-0.367	26.336	12.638	17.48	32.73	-0.340	0.039
Panel F: Indexes				**An.Ret. (%)**		**An.Vol. (%)**		**Skewn.**	**Ex. Kurt.**	**Correl. (%)**		**Info Ratio**	
SEI				3.01		48.40		0.094	2.283	-		-	
Bovespa				13.21		38.04		0.026	4.875	20.09		0.185	
DJIA				-7.07		28.03		-0.053	4.636	12.90		-0.191	
FTSE 100				-6.01		27.42		-0.009	5.374	24.34		-0.182	
S&P500				-9.46		30.07		-0.162	5.999	14.51		-0.235	
DJ UBS Energy-TR				-18.94		36.21		-0.166	1.102	43.83		-0.477	
Rogers Energy Commodity-TR				-6.15		41.11		-0.189	2.099	44.02		-0.192	

Table 5-5: Distributional statistics of portfolios' daily returns.

For further details, see notes in previous table.

		Quarterly Rebalancing											
		An. Ret (%)		An. Vol. (%)		Skewness		Ex. Kurtosis		Correl.		Info Ratio	
(K)	(λ)	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA	DE	GA
Panel A: Bovespa													
10	0.6	-6.79	6.38	35.68	38.32	-0.572	-0.588	7.688	7.146	23.76	27.67	-0.185	0.064
	0.8	-8.04	-7.48	35.39	36.15	-0.541	-0.499	7.696	7.198	23.72	26.04	-0.209	-0.200
	1	-8.88	-2.94	35.49	37.28	-0.537	-0.565	7.846	7.791	23.62	26.46	-0.225	-0.113
15	0.6	-7.36	-0.73	35.72	38.38	-0.578	-0.516	7.699	7.113	23.84	28.06	-0.196	-0.071
	0.8	-7.86	-4.05	35.49	37.33	-0.548	-0.620	7.910	7.932	23.79	26.89	-0.206	-0.134
	1	-8.14	-4.87	35.45	36.76	-0.532	-0.461	7.734	7.889	23.65	25.36	-0.211	-0.149
20	0.6	-7.49	8.27	35.73	38.45	-0.570	-0.494	7.661	7.896	23.95	26.36	-0.199	0.099
	0.8	-7.77	3.01	35.42	37.53	-0.544	-0.481	7.675	7.498	23.57	26.21	-0.204	0.000
	1	-8.62	-2.29	35.50	37.69	-0.534	-0.485	7.801	8.467	23.64	25.94	-0.220	-0.100
Panel B: DJIA													
10	0.6	-4.61	-3.13	19.76	22.72	0.543	0.329	12.944	9.405	8.96	13.36	-0.151	-0.121
	0.8	-5.14	-3.87	19.79	22.40	0.563	0.444	13.201	9.707	9.13	13.44	-0.161	-0.136
	1	-4.90	-1.33	19.76	22.87	0.630	0.437	13.884	10.343	8.97	14.63	-0.156	-0.086
15	0.6	-4.48	-1.33	19.85	22.44	0.536	0.405	12.659	10.195	9.01	13.63	-0.148	-0.086
	0.8	-4.83	-1.83	19.80	23.63	0.563	0.210	13.169	8.742	9.04	14.64	-0.155	-0.095
	1	-4.91	-4.12	19.87	24.36	0.600	0.475	13.712	12.793	8.97	15.65	-0.156	-0.141
20	0.6	-4.87	2.88	19.84	22.41	0.543	0.335	12.801	7.553	9.00	12.49	-0.156	-0.002
	0.8	-4.58	-5.36	19.83	24.40	0.542	0.355	13.054	9.969	9.07	16.10	-0.150	-0.165
	1	-4.75	1.72	19.86	23.42	0.587	0.526	13.684	10.842	8.93	15.57	-0.153	-0.026
Panel C: FTSE 100													
10	0.6	-8.03	5.68	25.87	28.61	0.040	-0.010	5.981	6.623	24.57	30.30	-0.225	0.056
	0.8	-8.96	-3.41	25.82	29.42	-0.019	0.082	5.743	8.084	24.11	30.01	-0.244	-0.132
	1	-8.62	-5.42	26.14	28.74	0.039	0.018	6.319	8.876	24.07	28.52	-0.236	-0.173
15	0.6	-8.78	-1.54	26.18	29.32	0.006	0.060	6.170	7.373	25.07	31.08	-0.241	-0.094
	0.8	-7.49	-0.19	26.03	28.89	0.004	-0.026	6.140	7.309	24.12	29.36	-0.214	-0.066
	1	-8.47	-5.78	26.26	30.48	-0.016	-0.106	6.310	7.594	24.01	30.57	-0.233	-0.180
20	0.6	-8.12	0.68	26.12	29.30	0.033	0.091	6.108	7.646	25.00	29.88	-0.228	-0.048
	0.8	-8.22	-0.64	26.12	29.07	-0.023	0.076	6.140	7.321	24.23	30.02	-0.229	-0.075
	1	-8.32	-2.24	26.17	29.43	-0.037	0.068	6.138	7.613	23.62	29.92	-0.230	-0.108
Panel D: UK Filter													
10	0.6	-14.16	2.21	18.43	23.56	-1.545	-0.908	11.532	5.806	22.81	29.94	-0.360	-0.017
	0.8	-12.40	-7.37	18.40	23.53	-1.540	-1.322	11.741	8.974	22.59	30.14	-0.323	-0.221
	1	-12.91	-23.42	18.47	22.11	-1.506	-1.353	11.692	9.453	22.38	28.14	-0.333	-0.560
15	0.6	-14.91	-5.58	18.45	23.98	-1.556	-0.908	11.403	4.967	23.06	28.91	-0.376	-0.181
	0.8	-14.81	-7.32	18.57	23.19	-1.602	-1.126	12.077	6.813	22.93	30.08	-0.373	-0.220
	1	-12.13	-8.57	18.59	24.84	-1.560	-0.947	11.759	5.099	22.40	30.45	-0.317	-0.245
20	0.6	-15.06	-8.22	18.38	24.71	-1.595	-1.115	11.618	6.180	22.97	29.35	-0.379	-0.237
	0.8	-14.55	-6.86	18.38	24.85	-1.600	-0.995	11.910	5.192	22.74	30.23	-0.368	-0.209
	1	-14.03	-9.44	18.48	23.93	-1.611	-1.037	11.846	6.240	22.36	30.48	-0.357	-0.265
Panel E: US Filter													
10	0.6	-6.16	9.29	20.51	26.77	-0.303	0.650	28.721	16.322	17.51	26.39	-0.187	0.129
	0.8	-5.70	9.06	20.64	24.56	-0.246	0.018	27.642	6.268	16.95	28.30	-0.177	0.127
	1	-6.23	-1.33	20.68	24.22	-0.289	-0.217	29.105	7.641	17.55	29.06	-0.188	-0.091

15	0.6	-5.12	18.48	20.57	26.87	-0.252	-0.104	28.952	5.516	17.48	25.97	-0.165	0.317
	0.8	-5.47	3.41	20.63	25.42	-0.200	-0.165	28.577	8.188	17.38	28.33	-0.172	0.008
	1	-5.62	8.15	20.73	24.86	-0.194	0.000	28.466	6.699	17.42	27.10	-0.175	0.107
20	0.6	-3.91	11.69	20.58	27.18	-0.289	-0.154	28.874	5.360	17.46	26.41	-0.141	0.178
	0.8	-5.27	12.30	20.65	26.32	-0.206	0.287	28.549	7.590	17.31	27.99	-0.168	0.193
	1	-5.87	6.19	20.84	26.44	-0.235	0.371	28.229	11.545	17.32	29.28	-0.180	0.067
Panel F: Indexes				**An.Ret. (%)**		**An.Vol. (%)**		**Skewn.**	**Ex. Kurt.**	**Correl. (%)**		**Info Ratio**	
SEI				3.01		48.40		0.094	2.283	-		-	
Bovespa				13.21		38.04		0.026	4.875	20.09		0.185	
DJIA				-7.07		28.03		-0.053	4.636	12.90		-0.191	
FTSE 100				-6.01		27.42		-0.009	5.374	24.34		-0.182	
S&P500				-9.46		30.07		-0.162	5.999	14.51		-0.235	
DJ UBS Energy-TR				-18.94		36.21		-0.166	1.102	43.83		-0.477	
Rogers Energy Commodity-TR				-6.15		41.11		-0.189	2.099	44.02		-0.192	

Furthermore, moving from no rebalancing to monthly rebalancing, the information ratios tend to go down in all cases, except in the case of the US Filter baskets for GA, and that of the UK Filter baskets for both DE and GA. This can be explained by the higher transaction costs which have a greater impact on the portfolios' returns, especially during falling markets. It can be argued that when rebalancing, the additional information available from the latest price data does make a difference on reducing the portfolios' volatility, but the small return improvement coupled with the rebalancing costs out-weighs the volatility benefits. Results are consistent for all cases for the risk-return trade-off λ. Among monthly and quarterly rebalancing the differences are relatively small, but the information ratios are in all cases higher for the monthly rebalanced portfolios, with only one exception for the FTSE selected baskets. This is an indication that greater capital efficiency can be achieved with the more frequent rebalancing. Under the buy-and-hold scenario, the best performance in terms of information ratios is reported for the Bovespa portfolios, and under both monthly and quarterly rebalancing it is reported for the US Filter portfolios. In most cases, negative information ratios are reported, indicating that these portfolios over the out-of-sample period under-perform the benchmark as they are associated with the lowest excess returns[36]. This observation can be explained by the fact that energy markets, as represented by the SEI, have been resistant to the recent economic recession, even though they have experienced one of their most severe up- and down-trends in their history.

[36] Note that investors who would have taken short positions on these baskets would realise the highest excess returns.

Historically it has been shown that commodities have had an equity-like risk/ return profile. while at the same time being negatively correlated with stocks. Moreover, financial activity in commodity markets during the past decade has grown too much in size relative to physical production, leading to non-commercial net long positions to be less influenced by the commodities' diversification benefits observed in the past (Domanski and Heath, 2007). Looking at tables 5-3, 5-4, and 5-5, it can be seen that when switching from quarterly to monthly rebalancing, correlations tend to marginally improve, with results being more profound for the baskets selected by the GA. The relatively low correlations of the selected equity portfolios with the SEI (between 9% and 33%) suggest that investors who want to participate in the energy sector can still benefit from the addition of the selected baskets to a well diversified portfolio of assets. This observation aligns with the findings of Buyuksahin et al. (2010) that the correlation between equity and commodity returns is not often greater than 30%, besides some noticeable fluctuation that occurs over time. Also, correlation is not the most appropriate performance measure, as it only measures the degree to which the selected equity baskets and the SEI move in tandem, and does not capture the magnitude of the returns and their trajectories over time. Moreover, as it is well documented in the literature and also verified in the results presented in this chapter, equity returns, represented by the financial indexes and the selected portfolios, deviate from a normal distribution displaying skewness and fat tails. The same is true for the returns of the SEI which exhibit positive skewness and relatively high excess kurtosis. Both futures commodity indexes have excess kurtosis similar to the SEI, with their skewness however being negative. Most equity portfolios selected by both the DE and GA exhibit negative skewness, indicating that the equity portfolios have more weight in the left tail of the distribution in contrast with the SEI that has more weight in the right tail.

Moreover, looking at table 5-6 it can be concluded that the strategy and methodology used in this thesis is much more efficient than a "naïve" strategy of randomly selected stocks, forming equally weighted portfolios constituted of 10, 15, and 20 stocks respectively. The evidence concur that this happens for both, achieving a good tracking performance (low RMSEs), and good returns relative to the SEI (positive or very small negative ERs). Under the "naïve" strategy there is a large dispersion of outcomes and no consistency, e.g. for the UK Filter portfolios with 10, 15 and 20 randomly selected socks, the respective information ratios are -0.62%, 0.09% and -0.12%.

Table 5-6: Performance of randomly selected portfolios.

This table presents a "Naïve" investment strategy of randomly selected stocks forming equally weighted portfolios consisting in each case by 10, 15 and 20 stocks, respectively. The stocks are selected from the same five equity pools used by the EAs, from a uniform distribution, thus giving equal probability for all stocks to be chosen.

	No Stocks	RMSE	ER (%)	An. Ret (%)	An. Vol. (%)	Skewness	Ex. Kurtosis	Correl. (%)	Info Ratio
	10	0.04	-0.01	1.32	45.20	-0.20	6.10	21.44	-0.03
Bovespa	**15**	0.04	0.03	9.73	45.31	-0.41	6.41	22.37	0.12
	20	0.04	0.02	7.80	42.79	-0.30	6.64	21.35	0.08
	10	0.04	-0.06	-12.05	35.64	-0.07	2.84	5.62	-0.26
DJIA	**15**	0.03	-0.02	-2.80	28.90	-0.19	4.03	12.56	-0.11
	20	0.03	-0.03	-3.62	30.57	-0.14	3.14	10.69	-0.12
	10	0.03	-0.04	-6.30	28.22	0.30	7.78	23.98	-0.19
FTSE 100	**15**	0.04	-0.09	-19.96	43.62	-0.02	4.35	25.15	-0.41
	20	0.03	-0.03	-5.80	41.27	-0.20	3.73	29.49	-0.16
	10	0.04	-0.14	-31.62	39.15	-2.00	20.65	18.78	-0.62
UK_FILTER	**15**	0.03	0.02	7.90	35.80	-0.54	4.71	26.38	0.09
	20	0.03	-0.02	-3.00	26.57	-0.48	3.52	24.72	-0.12
	10	0.03	-0.06	-10.97	38.48	-0.76	7.52	23.03	-0.26
US_FILTER	**15**	0.03	-0.04	-6.00	33.87	0.10	10.88	27.64	-0.18
	20	0.03	-0.04	-7.97	40.37	-0.44	7.40	29.29	-0.21

In addition, looking at the no rebalancing strategy in table 5-7 it can be observed that both algorithms in most cases do not utilise the maximum number of stocks allowed to select. The case is stronger for the GA selected portfolios. For instance, for all λ scenarios and for K=20, the maximum number of stocks selected in the case of the Bovespa, DJIA, and FTSE 100 stock pools is 8, 7, and 10 respectively. A general observation that can be made is that the algorithms tend to utilise almost the maximum number of available stocks when choosing from the UK Filter and US Filter pools. This can be justified by the fact that because only energy related stocks are included in the pools, there can be more stock combinations identified for inclusion in the selected portfolios, capable of tracking the performance of the SEI. Moreover, between the two evolutionary algorithms, the DE tends to use more stocks in the various selected portfolios, reaching the maximum number allowed most of the times. Finally, the DE is more stable in the number of stocks picked between the various cases of the risk/ return trade-off, whereas the GA tends to select portfolios quite different in terms of their composition. This can be confirmed by the much higher total number of stocks selected during all rebalancing frequencies, for both quarterly and monthly rebalancing strategies. For example, under monthly rebalancing and K=15, irrespectively of λ, the maximum total number of stocks that the DE selects is 49 and 45 for the FTSE 100 and US Filter baskets, while the GA selects 70 and 65 stocks respectively.

Table 5-7: Statistics of Portfolios (number of stocks used from algorithms).

Over the whole out-of sample period, "No Reb", "Q Reb" and "M Reb" shows the total number of stocks selected in each tracking portfolio i.e. under No rebalancing, Quarterly rebalancing and Monthly rebalancing, respectively. Note that "No Reb" is also the initial number of selected stocks for both "Q Reb" and "M Reb" because at t0=0 the estimation period is the same for all three rebalancing frequencies; hence, the number of stocks involved is identical. For further details, see also table 5-2.

		No Reb		Q Reb		M Reb	
(K)	(λ)	DE	GA	DE	GA	DE	GA
Panel A: Bovespa							
10	0.6	10	7	19	22	22	38
	0.8	10	5	19	25	25	34
	1	10	6	22	20	23	32
15	0.6	10	5	20	23	24	39
	0.8	11	6	20	24	25	36
	1	10	3	20	23	25	34
20	0.6	11	8	20	36	25	47
	0.8	10	8	21	30	25	42
	1	10	7	22	30	24	44
Panel B: DJIA							
10	0.6	10	5	24	23	31	30
	0.8	10	3	23	23	29	34
	1	10	3	23	27	27	38
15	0.6	15	4	31	28	35	37
	0.8	15	3	29	30	32	38
	1	15	2	29	27	32	38
20	0.6	17	6	31	36	36	42
	0.8	20	5	32	32	33	39
	1	19	7	33	35	32	43
Panel C: FTSE 100							
10	0.6	10	9	33	41	41	58
	0.8	10	4	32	43	40	61
	1	10	2	34	41	42	62
15	0.6	15	9	43	46	49	70
	0.8	15	7	40	47	46	66
	1	15	8	39	48	47	60
20	0.6	16	10	44	51	48	64
	0.8	17	10	42	50	48	63
	1	16	6	38	50	48	64
Panel D: UK Filter							
10	0.6	10	10	28	31	30	37
	0.8	10	5	26	24	29	37
	1	10	10	26	28	28	36
15	0.6	15	14	31	35	34	39
	0.8	15	15	30	37	33	40
	1	15	15	30	39	32	40
20	0.6	16	20	33	39	36	40
	0.8	17	20	30	40	34	41
	1	18	19	31	39	33	41
Panel E: US Filter							
10	0.6	10	10	25	43	38	54
	0.8	10	10	25	40	33	56

	1	10	10	29	45	34	64
15	0.6	15	11	34	44	44	61
	0.8	15	12	33	42	45	65
	1	15	15	35	51	40	64
20	0.6	16	12	35	50	43	65
	0.8	16	10	34	56	44	69
	1	16	19	34	58	39	72

5.6. Conclusions

In this chapter, a Geometric Average Spot Energy Index is constructed and then its performance is being reproduced with stock portfolios. This is achieved by investing in small baskets of equities, selected from five stock pools, the Dow Jones, FTSE 100, Bovespa Composite, and the UK and US Filters. The investment methodology used employs two advanced EAs, the GA and the DE. Both algorithms are self-adaptive stochastic optimization methods, superior to other rival approaches when applied to the index tracking problem. To test the performance of the tracking baskets three different rebalancing scenarios are examined, also taking transaction costs into consideration: a) buy-and-hold, b) monthly rebalancing, and c) quarterly rebalancing. For comparison reasons the performance of a "naïve" investment strategy of randomly selected stocks forming equally weighted portfolios is also reported.

It is found that energy commodities, as proxied by the SEI, can have equity-like returns, since they can be effectively tracked with stock portfolios selected by the investment methodology followed in this thesis. Overall, during the three-year period examined, which reflects a period before, during and towards the end of the recent global economic recession, an investor would realise positive returns by investing in commodities, as the SEI returns suggest. With the methodology employed that performance is closely replicated, and in the case of the energy related stock portfolios and those selected from the Bovespa equity pool, the benchmark index is even outperformed. In most cases there seem to be no major differences between the DE and GA selected portfolios, though the GA tends to select portfolios that have a lower tracking error. Both algorithms, in most cases, do not utilise the maximum number of stocks allowed to select, with the DE being more stable in the number of stocks picked between the various cases of the risk/ return trade-off; the GA tends to select portfolios quite different in terms of their composition.

On average, based on the results of this chapter, portfolios with 15 stocks and a risk-return trade-off value of 0.8 are the most desirable combination providing the best results for most tracking portfolios. Also, it is found that when rebalancing, the additional information available from the latest price data does make a difference on reducing the portfolios' volatility; the resulting return deterioration however, out-weighs the volatility benefits leading to smaller information ratios. Moving from the Buy and Hold strategy to Quarterly Rebalancing and then to the more frequent Monthly Rebalancing strategy, returns tend to deteriorate for most selected portfolios, by both the DE and the GA. Nonetheless, the same holds for the portfolios' volatilities that also tends to go down when moving from no rebalancing to the more frequent one. Between monthly and quarterly rebalancing the differences are relatively small in terms of the portfolios' return and volatility performance; however the information ratios are in almost all cases higher for the quarterly rebalanced portfolios. The only exception is for the US Filter in the case of the baskets selected by the GA. Thus, it is concluded that greater capital efficiency can be achieved with rebalancing, preferably every quarter, compared to the buy-and-hold strategy.

The investment approach proposed in this thesis, for tracking the performance of the energy sector with stocks selected by two innovative evolutionary algorithms, promotes a cost effective implementation and true investability. While most mutual funds cannot invest in commodities directly, they can track the performance of the SEI by investing in the stocks selected by the evolutionary algorithms used in this thesis. There are many investment houses around the globe that use evolutionary algorithms for tactical asset management[37]. The work and findings presented in this chapter can encourage asset and fund managers to recognise the importance of the energy sector and prompt them to set-up similar funds that will track the constructed Spot Energy Index. To that end, the proposed methodology suggests an effective, and at the same time, least expensive way to operate such a fund, giving the full flexibility of any investment style, long or short, that equities can provide.

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[37] First Quadrant a US based investment firm started using EAs in 1993 to manage its investments, at the time $5 billion USD allocated across 17 countries around the globe, claiming that have made substantial profits (Kieran, 1994).

Chapter 6.

6. Concluding remarks and future research

A thorough understanding of the dynamics of energy prices is of outmost importance when deciding to make an investment into energy commodities. There is a plethora of factors affecting the evolution of energy prices from both the supply and the demand side, which make the models and risk management ideas developed for the financial markets not directly applicable to the energy complex. What is more, the mean-reverting behaviour of energy commodities and their often unexpected and discontinued changes is well documented in the literature. This thesis proposes a modelling procedure that improves the fit of the models to better match the actual behaviour of the energy markets under investigation. In this thesis, a mean-reverting model with jumps is proposed that also incorporates two different speeds of mean reversion. One to capture the fast mean-reverting behaviour of returns after a jump occurs, and another for the slower mean reversion rate of the diffusive part of the model. The faster mean reversion rate after a jump occurs is used for a duration equal to the half-life of the jumps' returns. The model is also extended to incorporate time-varying volatility in the models' specification, modelled as a GARCH and an EGARCH process. Identifying any volatility asymmetries using the EGARCH specification can result in more efficient risk management applications by market practitioners. It can also enhance the accuracy of various widely used risk management techniques, such as Value-at-Risk (VaR). Furthermore, contrary to previous work, this thesis expands the choice of available models and the number of energy markets that these models are applied on.

The presence of a "leverage effect" for the spot log-price returns of WTI, Heating Oil, and Heating Oil–WTI crack spread is found. In contrast, for Gasoline, Gasoline–WTI crack spread, NG, Propane, PJM and the SEI the presence of an "inverse leverage" effect is indicated. The proposed modelling approach captures very well both the skewness and kurtosis of the actual series. Furthermore, the addition of the EGARCH (1,1) specification for the variance improves significantly the fit of the simulated returns to the actual distributions for most of the energy markets under investigation, and the SEI.

Moreover, the experience of the latest market shock highlights many shortcomings in the risk management practices used by market practitioners, who have clearly underestimated the frequency and magnitude of such extreme events. Many investors and financial managers did not have sufficiently strong modelling capabilities to comprehensively cover all asset classes in their portfolios, such as energy products and their derivative contracts. This led to a miscalculation of the actual risk of these assets and their hedging instruments, as in a number of cases they were based on wrong or flawed models. A consistent risk management framework and improved methods are required for measuring and modelling tail risk, while at the same time effectively assessing the integrity of the models.

The risk management models and framework proposed in this thesis move towards this direction by optimally capturing the behaviour of the energy markets under investigation, accounting not only for their frequency of occurrence but also for the volatility spikes and their clustering behaviour through time. Moreover, a solid two-stage back-testing and selection procedure is applied, so that all models are assessed on how well they can perform both statistically and economically. Following, the best model in terms of its VaR forecasting power is selected. Traditional VaR methods tend to underestimate the likelihood of extreme events because they usually assume normality or log-normality in the returns' behaviour. However, this thesis addresses the aforementioned shortcomings with the proposed modelling approach. The MC simulation models with the MRJD GARCH and EGARCH specifications, and the Hybrid MC-HS models, proposed for the first time in this thesis, control for the fat tails in energy returns as observed in their actual empirical distribution. Furthermore, by adding in the proposed methodology the Expected Shortfall notion as a measure to support the risk manager's decision, a more complete reflection of the expected loss in a worst-case scenario is provided.

This thesis finds that for the entire fuels complex, including the WTI, HO, Gasoline, and the two crack spreads with WTI, the MC simulations methodology under the MRJD specifications, followed by the Hybrid MC-HS models, pass all three statistical criteria from the first evaluation stage. At the same time they deliver the lowest LF at the second evaluation stage. These results are similar for both long and short trading positions. The only exceptions are for WTI and CS-HO-WTI, but only for the long trading positions, with the ARCH-type methodologies delivering the lowest Loss Function values.

The remarkable gains witnessed in commodity markets over the past decade, with this pattern accelerating in the last few years, has attracted investors' attention and led to an impressive growth of passive investment strategies in the commodity markets and in particular index investing. Moreover, index investing is becoming increasingly popular with empirical evidence supporting the idea that passive strategies are better than active ones especially in the longer term. The presence of high transaction costs in active strategies, and sometimes the overconfidence of investors in their predictions reduce profits substantially, leading to potential losses. Index tracking attempts to replicate the performance of an index, either by using full or partial replication. The latter is the most effective method and hence the most popular one. What is more, in general, there are three major ways of investing in a commodity index; first, choosing an index and replicating it by following the related Rule Book; second, investing in a fund which replicates the chosen index; finally, buying shares of an Exchange Traded Fund (ETF) having as a strategy to follow a commodity index. The latter is currently the most popular approach due to the numerous advantages that ETFs have over traditional investments, such as their wide range of investment applications, their flexibility as they can even be shorted without a preceding uptick, their cost effectiveness and tax efficiency.

Thus, the recently observed financialization of commodities and the increasing popularity of commodity index investing have pushed for more innovative investment strategies in the commodities markets, and especially for the energy-related products. One way of energy commodity investing is via futures contracts or energy commodity futures indexes. However, there are several risks and disadvantages associated with futures' based commodity indexes as discussed earlier in this thesis.

By following the investment approach proposed in this thesis, the aforementioned risks and disruptions can be eliminated, allowing for more flexibility to investors while at the same time giving them access to the excess returns and diversification benefits of energy commodities. Using as a performance benchmark for the energy markets the SEI, which allows investors to get closer to the underlying commodity price trends, and investing in the selected equity baskets investors overcome the shortcomings that futures indexes have. Using the evolutionary algorithms and the investment strategy suggested in this thesis, investors can optimally select their equity portfolios for tracking the SEI, without spending time, effort, and money trying to identify which stocks can simultaneously act as a profitable investment and a good commodity play. At the same time, investors are given the full flexibility of any investment style, either long or short, that equities can provide. The latter is very important for certain investor types like pension funds, which are usually not allowed to invest in futures contracts and other derivative products in alternative investment classes such as commodities. This is mostly due to strict regulation enforced by governments in their effort to protect peoples' savings.

Additionally, this thesis demonstrates that by applying the proposed investment strategy of tracking and trying to "beat" the constructed spot energy index, investors can gain superior results with reduced volatility and improved returns for their holding portfolios. This investment strategy adds depth to the capacity of investors' portfolios by providing them with the flexibility of investing in global securities markets, while extending their portfolios' span by including natural resources and tactical strategies that are not available via the futures markets/ indexes. It is also found that greater capital efficiency can be achieved with rebalancing, preferably every quarter, compared to the buy-and-hold strategy. The calculated information ratios are in almost all cases higher for the quarterly rebalanced portfolios. It is found that when moving from the buy-and-hold strategy to quarterly rebalancing and then to the more frequent monthly rebalancing strategy, returns, as well as portfolio volatilities, tend to deteriorate in most cases, for both the DE and the GA. Moreover, on average, the combination of portfolios with 15 stocks and a risk-return trade-off value of 0.8 is the most desirable one, providing the best results for most tracking portfolios. Overall, during the three-year period examined, which reflects a period before, during and towards the end of the recent global economic recession, an investor would realise positive returns by investing in commodities, as the SEI returns suggest. With the methodology employed in this thesis, SEI's performance is closely replicated, and in the case of the energy related stock portfolios as well as those selected from the Bovespa equity pool, the benchmark index in some instances is even outperformed.

It should be noted though that this research has not focused on a few important issues that still need to be thoroughly investigated in the literature. A potential avenue for future research is an extension of the proposed modelling approach to allow for a better understanding of the role of demand and supply conditions on the probability of jump occurrence, and in general on the distributional properties of the jumps. Some considerations for future research and improvement of the current research would also be to assess the VaR performance of the employed models for different time horizons, longer than one day. The additional information that might arise by assessing weekly or monthly VaR forecasts could lead to setting-up improved energy risk management policies by governments and regulators. The proposed VaR estimates could also be used for setting the margin requirements in the growing energy derivatives market, and more importantly for the energy forwards, futures, and options contracts that are widely used for both hedging and speculation purposes by many industrial players, commodity and investment houses. Additionally, for hedging purposes, in order for the proposed models to be adapted by practitioners, transactions costs associated with hedging portfolios should also be considered. Moreover, a possible extension of the work done on the VaR calculations of the various energy portfolios would be to use the VaR estimates as a tool for portfolio optimization. The VaR estimates produced in this thesis could be used as a risk management tool to build a special optimal portfolio that will then be used as the benchmark for the proposed index tracking investment methodology. Another future extension of this research could be to implement various long/short strategies using the proposed index tracking methodology. Then the performance of these strategies can be tested as to whether they can improve the risk/ return profile of traditional asset portfolios. Industry practitioners such as commodity trading advisors and commodity pool operators regularly use investment strategies that besides long-only, can also be systematic long/short, using leverage to take the short positions.

An additional limitation of this research is that it does not consider any futures or other derivatives contracts to test the proposed modelling framework. The latter can be further investigated in future research, where the forward curve approach could also be used as an alternative modelling framework to the spot price models. Based on a data set of historical forward curves for all the NYMEX traded energy contracts, the number of independent factors needed to model adequately the forward curve's dynamic evolution could be determined, using the Principals Component Analysis (PCA) technique. The PCA technique could be used in the context of a multi-factor forward curve model that could capture the evolution of the forward curve for each one of the energy contracts that is examined in this thesis. Then, the ability of the spot models proposed in this thesis, and the forward curve based models could be compared in terms of their ability to price the respective NYMEX traded energy options.

Furthermore, this thesis does not address the issue of valuing real assets based on real options theory. The framework employed follows the approach where the main source of uncertainty is the price of the commodity itself, whereas it could prove more interesting to introduce a number of other uncertainties into the valuation process. Hence, a further extension of this research could be the application of MC simulations for pricing real options. Many practitioners are starting to treat energy related fixed assets as derivative instruments using the real options analysis. This grasp of the derivatives point of view gives a greater understanding of the asset's value, compared with the most traditional Net Present Value analysis. Under this approach, to be able to price this "derivative", plausible pricing scenarios need to be assumed, and the appropriate stochastic process needs to be used for the simulated valuations to be realistic.

In sum, it is acknowledged that this thesis has certain limitations and caveats which must be taken into consideration when interpreting its findings and results. Furthermore, some of these limitations can constitute a fertile ground for further research that could potentially strengthen the findings and outcomes of this thesis. They could also add to the existing literature regarding the best approach for modelling spot prices, the application of effective risk management practises, and the development of innovative investment strategies in the energy commodity markets.

Chapter 7.

7. Bibliography and references

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Chapter 8.

8. Appendix

8.1. Industry Classification Benchmark (ICB)

The Industry Classification Benchmark (ICB) is a company classification system developed jointly by Dow Jones and FTSE. It is used to segregate markets into a number of sectors within the macro-economy. The ICB uses a system of 10 industries, partitioned into 19 super sectors, which are further divided into 41 sectors, which then contain 114 subsectors.

The principal aim of the ICB is to categorize individual companies into subsectors based primarily on a company's source of revenue or where it constitutes the majority of revenue. If a company is equally divided amongst several distinct subsectors, the judging panel from both Dow Jones and FTSE makes a final decision. Firms may appeal their classification at any time.

The ICB is used globally (though not universally) to divide the market into increasingly specific categories, allowing investors to compare industry trends between well-defined subsectors. The ICB replaced the old classification systems used previously by Dow Jones and FTSE on 3 January, 2006, and is used today by the NASDAQ, NYSE and several other markets around the globe. All ICB sectors are represented on the New York Stock Exchange except Equity Investment Instruments (8980) and Non-equity Investment Instruments (8990).

Table 8-1 below presents the ICB codes used for filtering all US and UK stock markets, creating the two energy-related stock pools named US Filter and UK Filter, respectively.

Table 8-1: Industry Classification Benchmark (ICB) codes

Industry	**Super-sector**	**Sector**	**Sub-sector**
0001 Oil & Gas	0500 Oil & Gas	0530 Oil & Gas Producers	0533 Exploration & Production
			0537 Integrated Oil & Gas
		0570 Oil Equipment, Services & Distribution	0573 Oil Equipment & Services
			0577 Pipelines
		0580 Alternative Energy	0583 Renewable Energy Equipment
			0587 Alternative Fuels
7000 Utilities	7500 Utilities	7530 Electricity	7535 Conventional Electricity
			7537 Alternative Electricity

8.2. Stocks used in all five equity pools

The table below includes all stocks used in the five equity pools from which the final stock portfolios were selected by the two algorithms, GA and DE, respectively.

Table 8-2: List of all stocks used in each pool for the selection of the tracking stock portfolios.

FTSE 100 (98 stocks in total)	**DJIA 65 (65 stocks in total)**	**Bovespa (56 stocks in total)**	**UK Energy Filter (54 stocks in total)**	**US Energy Filter (89 stocks in total)**
3I GROUP	3M	ALL AMER LAT UNT	AFREN	ALON USA ENERGY
ADMIRAL GROUP	AES	AMBEV PN	ALKANE ENERGY	AMERICAN OIL & GAS
ALLIANCE TRUST	ALCOA	ARACRUZ PNB	ANDES ENERGIA	ARENA RES.
AMEC	ALEX.& BALDWIN	BANCO BRASIL ON	ASCENT RESOURCES	ATLAS AMERICA
ANGLO AMERICAN	AMER.ELEC.PWR.	BRADESCO PN	BALTIC OIL TERMINALS	ATP OIL&GAS
ANTOFAGASTA	AMERICAN EXPRESS	BRADESPAR PN	BORDERS & SOUTHERN PTL.	BASIC ENERGY SVS.
ASSOCIATED BRIT.FOODS	AMR	BRASIL TELCOM PARTP.PN	BOWLEVEN	BGE CAPITAL TST.II
ASTRAZENECA	AT&T	BRASIL TELECOM PN	CDS OIL & GAS GROUP	BILL BARRETT
AUTONOMY CORP.	BANK OF AMERICA	BRASKEM PNA	CERES POWER HOLDINGS	BOARDWALK PIPELINE PTNS.
AVIVA	BOEING	BRF FOODS ON	CIRCLE OIL	BRONCO DRILLING
BAE SYSTEMS	BURL.NTHN.SANTA FE C	CCR RODOVIAS ON	CLIPPER WINDPOWER (REGS)	CANO PETROLEUM
BALFOUR BEATTY	CATERPILLAR	CELESC PNB	D1 OILS	CHINA NTH.ET.PTL.HDG.
BARCLAYS	CENTERPOINT EN.	CEMIG PN	DRAX GROUP	CIMAREX EN.
BG GROUP	CH ROBINSON WWD.	COMGAS PNA	EGDON RESOURCES	CNX GAS
BHP BILLITON	CHEVRON	COMPANHIA BRASL.DISTB. PNA	EMPYREAN ENERGY	COMPLETE PRDN.SVS.
BP	CISCO SYSTEMS	COPEL PNB	ENCORE OIL	COPANO ENERGY
BRITISH AIRWAYS	COCA COLA	COSAN ON	EUROPA OIL & GAS (HDG.)	CROSSTEX EN.
BRITISH AMERICAN TOBACCO	CON-WAY	CPFL ENERGIA ON	FALKLAND OIL & GAS	CROSSTEX EN.SHBI

BRITISH LAND	CONSOLIDAT ED EDISON	CYRELA REALT ON	FAROE PETROLEUM	CUBIC ENERGY
BRITISH SKY BCAST.GROUP	CONT.AIRL.B	DURATEX PN	FORUM ENERGY	DAYSTAR TECHS.
BT GROUP	CSX	ELETROBRA S ON	FRONTERA RESOURCES	DCP MIDSTREAM PTNS.
BUNZL	DOMINION RES.	ELETROBRA S PNB	GETECH GROUP	DELEK US HOLDINGS
CABLE & WIRELESS	DUKE ENERGY	EMBRAER ON	GLOBAL ENERGY DEV.	DRESSER-RAND GROUP
CADBURY	E I DU PONT DE NEMOURS	GAFISA ON	GOOD ENERGY GROUP	DTE EN.TST.II GTD TOPRS
CAIRN ENERGY	EDISON INTL.	GERDAU PN	GULFSANDS PETROLEUM	DUNE ENERGY
CAPITA GROUP	EXELON	GOL PN	HALLIN MAR.SUBSEA INTL.	ENBRIDGE EN.MAN.
CARNIVAL	EXPEDITOR INTL.OF WASH.	ITAUSA PN	HARDY OIL & GAS	ENCORE ACQ.
CENTRICA	EXXON MOBIL	ITAUUNIBAN CO PN	HYDRODEC GROUP	ENDEAVOUR INTL.
COBHAM	FEDEX	KLABIN SA PN	INDEPENDENT RESOURCES	ENERGY TRANSFER EQ.
COMPASS GROUP	FIRSTENERGY	LIGHT ON	IPSA GROUP	ENTERGY MS.6% 1ST.MGE. BDS.
DIAGEO	FPL GROUP	LOJAS AMERIC PN	ISLAND OIL AND GAS	ENTERPRISE GROUP HDG.
FOREIGN & COLONIAL	GATX	LOJAS RENNER ON	ITM POWER	EVERGREEN SOLAR
FRIENDS PROVIDENT GROUP	GENERAL ELECTRIC	METALURGI CA GERDAU PN	LANSDOWNE OIL & GAS	EXCO RESOURCES
G4S	HEWLETT-PACKARD	NATURA ON	MAX PETROLEUM	FMC TECHNOLOGI ES
GLAXOSMITHKLI NE	HOME DEPOT	NET PN	MEDITERRANE AN OIL & GAS	GASCO EN.
HAMMERSON	HUNT JB TRANSPORT SVS.	PETROBRAS ON	MERIDIAN PETROLEUM	GEOPETRO RESOURCES
HOME RETAIL GROUP	INTEL	PETROBRAS PN	NAUTICAL PETROLEUM	GLOBAL ENERGY HDG.GP.
HSBC HDG. (ORD $0.50)	INTERNATION AL BUS.MCHS.	ROSSI RESID ON	NOVERA ENERGY (LON)	GLOBAL PARTNERS UNITS
ICAP	JETBLUE AIRWAYS	SABESP ON	OFFS.HYDROCA RBON MAPPING	GMX RES.
ICTL.HTLS.GP.	JOHNSON & JOHNSON	SADIA PN	PANTHEON RESOURCES	GRAN TIERRA ENERGY
IMPERIAL	JP MORGAN	SIDER.NACI	PETROFAC	GREEN

TOBACCO GP.	CHASE & CO.	ONAL ON		PLAINS RENEW.EN.
INMARSAT	KRAFT FOODS	SOUZA CRUZ ON	PETROLATINA ENERGY	HECO CAPITAL TST.III 6.5%
INTERNATIONAL POWER	LANDSTAR SYSTEM	TAM PN	PLEXUS HOLDINGS	HERCULES OFFSHORE
INTERTEK GROUP	MCDONALDS	TELE NRLES.PART P.ON	REGAL PETROLEUM	HILAND PARTNERS
INVENSYS	MERCK & CO.	TELE NRLES.PART P.PN	RENEWABLE ENERGY GNRTN.	HOKU SCIENTIFIC
JOHNSON MATTHEY	MICROSOFT	TELEMAR NRLES.PNA	RENEWABLE ENERGY HDG.	HOLLY ENERGY PTNS.
KAZAKHMYS	NISOURCE	TELESP PN	RHEOCHEM	HORNBECK OFFS.SVS.
KINGFISHER	NORFOLK SOUTHERN	TIM PART ON	ROCKHOPPER EXPLORATION	HOUSTON AMERICAN EN.
LAND SECURITIES GROUP	OVERSEAS SHIPHLDG.GP.	TIM PART PN	RURELEC	ITC HOLDINGS
LEGAL & GENERAL	PFIZER	TRAN PAULIST PN	SERICA ENERGY (LON)	KINDER MORGAN MAN.
LIBERTY INTL.	PG&E	ULTRAPAR PARTP.PN	SOVEREIGN OILFIELD GP.	LINN ENERGY
LLOYDS BANKING GROUP	PROCTER & GAMBLE	USIMINAS ON	VENTURE PRODUCTION	MAGELLAN MIDSTREAM HDG.
LONDON STOCK EX.GROUP	PUB.SER.ENTE R.GP.	USIMINAS PNA	VICTORIA OIL & GAS	MAGELLAN MIDSTREAM PTNS. UTS.
LONMIN	RYDER SYSTEM	VALE ON	WOOD GROUP (JOHN)	MARINER ENERGY
MAN GROUP	SOUTHERN	VALE PNA		MARTIN MIDSTREAM PTNS.
MARKS & SPENCER GROUP	SOUTHWEST AIRLINES	VIVO PN		MIRANT
MORRISON(WM)SP MKTS.	TRAVELERS COS.			MMC ENERGY
NATIONAL GRID	UNION PACIFIC			NATURAL GAS SVS.GP.
NEXT	UNITED PARCEL SER.			NEW GNRTN.BIFL.H DG.
OLD MUTUAL	UNITED TECHNOLOGI ES			NORTHWESTE RN
PEARSON	VERIZON COMMUNICAT IONS			NRG ENERGY
PENNON GROUP	WAL MART			NUSTAR

	STORES			ENERGY LP
PETROFAC	WALT DISNEY			OCEAN POWER TECHS.
PRUDENTIAL	WILLIAMS COS.			OIL STS.INTL.
RANDGOLD RESOURCES	YRC WORLDWIDE			OILSANDS QUEST
RECKITT BENCKISER GROUP				ORMAT TECHS.
REED ELSEVIER				PLAINS EXP.& PRDN.
REXAM				PORTLAND GEN.ELEC.
RIO TINTO				RAM ENERGY RESOURCES
ROLLS-ROYCE GROUP				RASER TECHS.
ROYAL BANK OF SCTL.GP.				REGENCY ENERGY PTNS.
ROYAL DUTCH SHELL A(LON)				RIO VISTA EN.PTNS.LP.
ROYAL DUTCH SHELL B				ROSETTA RESOURCES
RSA INSURANCE GROUP				RRI ENERGY
SABMILLER				SOUTH TEXAS OIL
SAGE GROUP				SUNOCO LOGIST.PTNS. LP
SAINSBURY (J)				SUNPOWER 'A'
SCHRODERS				SUPERIOR WELL SVS.
SCHRODERS NV				TEEKAY LNG PARTNERS
SCOT.& SOUTHERN ENERGY				TETON ENERGY
SERCO GROUP				TRANSMONTAIGNE PTNS.
SEVERN TRENT				TRICO MARINE SVS.
SHIRE				ULTRA PTL.
SMITH & NEPHEW				UNION DRILLING
SMITHS GROUP				W&T OFFSHORE
STANDARD CHARTERED				WARREN RESOURCES
TESCO				WESTERN REFINING

THOMAS COOK GROUP				WHITING PTL.
TUI TRAVEL				WILLIAMS PARTNERS
TULLOW OIL				
UNILEVER (UK)				
UNITED UTILITIES GROUP				
VEDANTA RESOURCES				
VODAFONE GROUP				
WOLSELEY				
WPP				
XSTRATA				