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INVESTIGATION OF CAUSALITY BETWEEN SPOT AND DERIVATIVES MARKETS: THE CASE OF COMMODITIES AND FINANCIAL INDICES

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CERTIFICATE OF AUTHORSHIP

I, Ioannis Drougalas, certify that I am responsible for the work submitted in this dissertation, that the original work is my own except as specified in acknowledgements and that neither the thesis nor the original work therein has been submitted to this, or any other institution, for a degree.

To the best of my knowledge, I cited correctly all references which I was assisted by with intellectual material, including tables, illustrations or graphs.

ABSTRACT

This study examines linear and non-linear Granger causality between spot and futures markets. For this purpose, daily observations from January 2010 to November 2019 for four commodities, namely WTI oil, natural gas, gold and silver and for four financial indices, namely the DAX30, CAC40, SP500 and Nasdaq100 are used. For each asset, futures contracts of various maturities are considered and are matched in pairs (bivariate) and jointly (multivariate) with the respective spot value. Linear and non-linear causal dynamics are investigated with the conventional VAR/VEC modelling and the Diks and Panchenko (2006) non-parametric test respectively. Regarding commodities, linear examination reveals that futures lead spot market in almost all pairs for the cases of gas, gold and silver, but there is either spot dominance or bidirectional lead in the pairs of WTI oil. The non-linear approach further enhances the leading role of futures for all commodities but also uncovers non-linear feedback mechanisms for a few pairs. Regarding financial indices, linear causal dynamics are weak for the DAX30, but there is evidence that spot linearly leads futures for the CAC40 and that futures linearly Granger-cause the spot for the two US indices. Under the non-linear approach significant bidirectional causal channels emerged for all pairs and all financial indices.

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Introduction

Spot and futures markets are closely related as futures contracts essentially refer to the underlying spot assets. As part of the interdependencies between them, causality relationships interest both academics and practitioners as they are tightly linked with two important concepts of financial markets; the asset price discovery process and market efficiency. Both concepts are based on the arrival and transmission of new information to markets and the speed of its integration into prices. Spot and futures markets "compete", regarding the absorption of new information, and the link between them create differential dynamics and set the framework for the direction of informational transmissions and for the dominant and satellite market roles. In particular, causal effects, as those are defined in the Granger context, can be used to answer the question of which market drives the price discovery process as well as the question of which market is relatively more efficient.

Investigation of causality could help investors realize and employ appropriate investment strategies. Hedgers, the primary investors of futures markets, can assess the risk management efficiency of futures contracts. Speculators can outperform the passive portfolio if it is found that either the spot or futures market leads and is able to predict the other and if an appropriate trading strategy can be devised considering such lead-lag relationships. Market regulators are also interested in causality relationships as they can improve the functionality of the markets through their understanding of the traders' incentives and keep the balance between hedgers and speculators.

Theoretically, in frictionless and efficient markets, a new set of information is absorbed instantly. Hence, spot and futures markets should appear equally efficient and neither market should drive the other. However, solid theoretical arguments are presented by advocates who support the hypothesis that spot markets drive futures markets. The reverse hypothesis is also rigidly supported. There are also proponents who embrace the premise that both types of markets lead each other in time-varying regimes. Empirical evidence also has not yet produced a decisive conclusion as previous research in causality presented inconsistent results. While most of the studies found that futures markets drive spot markets, there is a substantial number of papers which indicate that spot markets drive futures markets or that both types of markets lead each other through a feedback mechanism. Furthermore, contradictions occur among studies examining the same asset due to different data sets and methodologies used. Hence the puzzle remains regarding spot and futures causal dynamics.

This work tries to answer the questions regarding price discovery and market efficiency by the investigation of Granger causality between spot and futures markets. Specifically, four commodities, namely WTI oil, natural gas, gold and silver, and four financial indices, namely the DAX30, CAC40, SP500 and Nasdaq100 are utilized for this purpose. Two to four contracts of different maturities are considered for each asset. Apart from the conventional linear Granger causality which is examined through the appropriate VAR/VEC models, the non-linear Granger causality is also examined through the Diks and Panchenko (2006) non-parametric approach, due to the ever-growing evidence of non-linear causal dynamics in recent papers.

Chapter 1 presents the foundations of derivatives theory including forwards, futures, options and swaps, as well as the theoretical background of interdependencies and causal dynamics between spot and futures markets. The last part of the chapter summarizes the literature review in the topic which is used as a basis for comparison for this work.

Chapter 2 refers to the empirical part. This chapter presents the data used, the methodology employed and the test results derived. The last part of the chapter is concerned with the discussion and comparison of the results with those of similar studies and their potential implications with the theory presented in chapter 1.

CHAPTER 1

1.1 DERIVATIVES THEORY

1.1.1 Definition and a Brief History of Derivatives

Derivatives are financial instruments which are built upon -derived from- underlying assets, such as stocks, indices, currency exchange rates, bonds, and commodities. They are bilateral agreements whose value depends on the value of the corresponding underlying assets. Derivatives are traded either on exchange markets or on over the counter (OTC) markets.

Through a derivative agreement, market or credit risks can be transferred from one counterparty to the other. Each of the two counterparties evaluates and interprets risks differently considering its overall portfolio, so both sides may feel the agreement is favorable. Besides, traders are willing to be exposed to risks anyway for an appealing price or return with regard to their risk preferences.

There are two positions in a derivative contract. The buyer or holder of the contract has the long position. The seller or writer of the contract has the short position. The long position trader benefits when the value of the contract increases, while the short position trader benefits when the value of the contract decreases. An important difference between derivatives and other instruments traded on financial markets is that the former constitute a zero sum game that is the profits of one counterparty come up as losses of the other party and profits and losses altogether sum up to zero.

In a nutshell, the main derivative contract types are:

- Forwards and Futures
- Options
- Swaps

Forwards, futures and options are bilateral agreements for the sale and delivery of a specific quantity of the underlying asset in a predetermined price and date. Swaps are bilateral agreements for the exchange of fixed cash flows for a certain time duration. For forwards, futures and swaps, contract enforcement applies for both the buyer and the seller, while for options it only applies for the seller; the holder of an option may opt to walk away from the contract. All mentioned contracts transfer market risks.

Credit derivatives, which transfer default risks, are not presented here for they are out of the scope of this work.

Derivatives is not a new financial concept. Evidence of contracts for future delivery of goods are found on clay plates, dated back in the 19th century B.C. in the region of Mesopotamia. Phoenicians and Greeks used to pre-sell their traded goods in predetermined prices and deliver them at some point in the future, although Greek laws imposed restrictions on such practices. In his *Politics*, Aristotle mentions that Thales, after forecasting for an excellent summer harvest season, agreed with olive press owners that he pre-pays a deposit for the right to use their presses after harvest. Thales afterwards rented the highly demanded presses to harvesters, thus gaining considerable profits via the first recorded option-like agreement. During Roman times, Pompey used pre-arrangements with merchants in order to secure goods and keep up with the ever-growing urbanization of Rome, though generally Roman laws, influenced by Greek culture, favored spot transactions (Kummer and Pauletto, 2012). In medieval Italy, the first organized markets, such as the Periodical Fair regulated by the Church, emerged. Pre-arrangements upon traded goods in those markets helped merchants to optimize their logistics and mitigate travel dangers, a prevailing issue of that time.

During the Renaissance, in the midst of European cultural and economic prosperity, the first security markets and organized secondary markets appeared throughout the Italian kingdoms. Derivative contracts, written until that time on commodities, expanded on city bonds (monti shares) and bills of exchange. Financial modernization spread in Northern Europe, particularly in the commercial cities of Antwerp, Bruges and Amsterdam. In the middle of the 16th century, a decisive innovation took place; delivery of the underlying asset of derivative contracts was not compulsory anymore. Instead, the contracts could be settled in cash by evaluating the difference between the prearranged price and the spot price of the asset. These *contracts for differences* became popular as a means of trading for the shares of the prominent of that time Dutch East India and Dutch West India companies (Weber, 2008). In the 1630s, in the midst of the Dutch golden age, the famous tulip mania period surfaced and Dutch markets turned to the sought after tulip bulbs, via spot and derivative trading. Domestic as well as French demand for the enchanting bulbs caused mass speculation and skyrocketed the tulip price, but, as there were no margins or other obligations for speculators, derivative contracts defaulted and the tulip price collapsed in 1637, thus completing the first recorded financial bubble in history. In 1688, in *Confusion de Confusiones*, the first ever book written about exchange markets, Joseph de la Vega implicitly analysed call and put options as well as forward contracts.

Meanwhile, in the middle of the 17^{th} century, Osaka became the prevailing rice trading center of Japan and derivative trading started to blossom. Large amounts of rice were sold in auctions, but rice was not delivered immediately; instead *rice bills* were issued that determined price, delivery date, and rice quantity. Additionally, feudal lords in need of immediate cash flows issued *prepay bills* selling rice crops of future seasons. Shortly, merchants started trading on both of those bills which resembled modern forward contracts. Although Osaka authorities soon prohibited bill trading which was considered as pure gambling, merchants still managed to maintain an active informal market. Early in the 18^{th} century, legislation regarding derivative trading became conveniently flexible. When rice price was high, bill trading was restricted, whereas restrictions were loose when rice price was low. In 1715 Dojima Rice Exchange was officially recognized by Shogun. The exchange had several features of modern exchanges. Contracts traded resembled nowadays forwards and futures with high level of standardization and they were cleared at regular time intervals. Also, participants had to be registered in the clearing house which carried default risks of the counterparties (Kummer and Pauletto, 2012).

In the late 17^{th} century, Dutch financial experts followed William of Orange in England after his victory in Glorious Revolution and sowed the seed for the first derivatives markets in London. Dutch financial knowledge and the emergence of the British Empire as the dominant naval commercial power enabled English markets to expand and drove London to grow into the leading trading center of Europe. London markets met their first bubble in 1720, when the backed by the government South Sea Company failed to meet public expectations and after options trading for speculation purposes had irrationally risen the share price. The South Sea Company bubble had more consequences in British economy than the tulip bubble had in Dutch economy, for London markets stipulated stricter contract enforcement (Weber, 2008). To avoid similar incidents, the British Parliament forbade derivatives on securities, yet British continued trading on derivative contracts with honor being the only assurance in effect. A similar situation occurred at about the same time in Paris markets. The promising Compagnie Perpetuelle des Indes crashed after intensive speculation through derivatives, damaging French economy and leading the State Council to inhibit derivative trading both in securities and commodities. French reacted in the same way as British did, carrying prohibited trading from exchange markets to nearby restaurants and cafes.

After the defeat of Napoleon in 1815, issuance of French government bonds for war reparations, combined with stabilization of franc achieved in previous years and positive investors' sentiment, created fertile grounds for derivative trading to flourish in Parisian markets, although restrictions dictated a century ago were still in effect.

Though the first exchanges started to appear in the 16th century in the Germanic region, derivative trading developed two centuries later. In the 19th century, following the French pattern, trading on city bonds, as well as, banks, railway and industrial enterprises shares enabled German cities, particularly Frankfurt and Berlin to catch up with the leading European economic centers. By that time, several publications on derivatives were available and attracted public attention, though most authors' law background and insufficient financial expertise added little value for investors, even compared with de la Vega's seminal work written more than a hundred years ago. Weber (2008) argues that the lack of understanding of derivative strategies and combinations hindered further development in the corresponding markets.

In 1848 and 1898 respectively, the Chicago Board of Trade (CBOT) and the Chicago Mercantile Exchange (CME) were founded in the United States giving birth to the modern form of derivative trading. CBOT was initially establish to facilitate the transactions between merchants and agricultural producers, but trading on futures, or *to-arrive contracts* as known by that time, started after a few years luring speculators into the market. In 1858 the contracts were solidly standardized by classifying grades of grain. Two important innovations took place in about 1865 when a clearing house was established and margins were implemented in the contract transaction procedure. CME and CBOT merged in 2007 to create CME Group which now owns the Commodity Exchange Inc. (COMEX), New York Mercantile Exchange (NYMEX) and Kansas City Board of Trade (KCBT) as well (Hull, 2018).

Roughly flicking through derivatives history, there are two distinctive points that could be made. Firstly, derivatives conceptually started as a risk management tool for either merchants and farmers or political leaders and their states and with respect to the corresponding historic framework and its risks. Speculation appeared later on as an after-effect. But it was speculation that led to consequences, such as bubbles and volatility, associated at least partially with derivatives. Secondly, due to those issues, governments and policy makers periodically made efforts to control derivative markets and massive trading for speculative purposes mainly by imposing restrictive regulations. In most cases, traders slipped their way off these measures and continued to trade, but there is no evidence of whether trading was improved or not after implementing regulative changes. Legislation in derivative trading remains a controversial topic even nowadays, especially for developing economic markets.

1.1.2 Derivatives Markets

As mentioned before, derivatives nowadays are traded on derivatives exchange markets and over the counter markets.

In **derivatives exchanges**, investors trade on standardized contracts with regard to the transaction price, the quantity of the underlying asset to be traded and the delivery date. In some contracts, such as those for agricultural commodities, the quality of the product as well as the location in which physical delivery will take place is also specified in contract terms.

An important feature of a derivatives exchange is the clearing house. It acts as an intermediate player between the two counterparties of a derivative contract. In fact, the two investors involved in the contract may not even know each other. Technically speaking, if investor A wants to take the long position of a contract and investor B wants to take the short position, two contracts will be realized; a contract between investor A (long position) and the clearing house (short position) and a contract between investor B (short position) and the clearing house (long position). Thus, the investors acquire the desired respective positions and the two opposite positions acquired by the clearing house are actually nullified. The main advantage of this procedure is credit risk mitigation for both investors, as they do not have to worry about the creditworthiness of each other.

The traditional operating system of derivatives exchanges has been the open outcry system. Traders meet in a physical place and agreements are realized via shouting and gestures. In recent years however, electronic trading has gained ground at the expense of the outcry system. A step further, high frequency and often unmanned algorithmic trading through Application Programming Interfaces is the last technological implementation in derivative exchanges (Kosowski and Neftci, 2015).

In 2018, about 30 billion derivatives were traded in exchange markets worldwide, with stock indices futures and options being the most traded contracts (WFE, 2019). The CME Group and the National Stock Exchange of India are the most active markets.

In the case of **over the counter markets**, contracts are not necessarily standardized. The benefit of contract customization attracts big players, such as financial institutions and hedge funds in OTC markets. Here, the contract is agreed directly between the two counterparties. The participants know each other and they end up with a customized contract that fulfills their needs. A central counterparty (CCP) takes the place of the clearing house, however the CCP does not always stand between the two parties; the contract can be realized bilaterally without the interception of the CCP. After the collapse of Lehman Brothers in 2008, regulation of OTC markets became stricter in order to improve efficiency and transparency and to reduce systemic risk, that is the ripple effect caused by a default, such that of Lehman Brothers. According to Hull (2018), critical changes in the regulation of the United States OTC markets include:

- In the case of standardized contracts, specialized electronic platforms called SEFs are used on which quotes are posted and trading takes place.
- CCP must be involved in the trading of standardized contracts.
- Trading of both standardized and non-standardized derivatives must be registered in a central system.

As of December 2018, the total notional amount of derivatives traded on OTC markets was 544 trillion dollars and gross market value was 9.7 trillion dollars (BIS, 2019). Since December 2008 when it hit the peak of 35 trillion dollars, gross market value has been declining, partially as a result of stricter regulations after the recent economic crisis. Interest rates contracts are by far the most traded derivatives on OTC markets, both in principal and market value, followed by currency exchange rates contracts.

1.1.3 Types of Investors in Derivatives Markets

Derivatives markets attract many investors, thus achieving high liquidity which facilitates transactions. Regarding their motives for entering the market, investors can be classified in three categories: hedgers, speculators and arbitrageurs.

Hedgers desire to mitigate risks that they deal with in spot markets. From the perspective of the derivatives market makers, hedgers are theoretically the elementary investors, hence risk management performance is at the core of a derivatives market functions. However, from the perspective of hedgers, derivatives markets is the secondary domain; spot markets remain hedgers' primary domain. They use derivatives to invest in unfavorable future movements of their primary spot position. The underlying asset of the derivative can be either exactly the same spot asset of interest or another asset with similar price behavior (cross-hedging). A typical example of hedger could be an oil production company which of course would worry to see oil prices declining. Thus, it will acquire such a position in derivatives markets that will be profitable if oil prices decline indeed. Any losses in the spot market would be totally or partially nullified by the position taken in derivatives markets. Another example could be a company that exports products internationally and desires to lock in a specific currency exchange rate, for fear that the national currency will be overvalued and future payments made in foreign currency will be devalued. It should be noted however, that hedging does not guarantee a better result. The spot and derivative positions have to oppose each other. Hedging mitigates losses in case of unfavorable spot movements, but it also narrows profits in case of favorable spot movements.

Speculators do not have the same concerns as hedgers do. They essentially try to predict price movements and gamble in derivatives markets, mainly via futures or options. They take long positions if they forecast positive price changes and short positions in the opposite case, albeit the strategies followed are generally more composite. Derivatives are ideal for speculation as they are leveraged instruments requiring less initial capital than spot assets. Also, considering Kaldor's (1939) argument that speculation blossoms in markets of high level of standardization and for assets with low carrying expenses, in terms of durability and storage, it is unsurprising that speculators are involved in derivatives markets. A typical example of speculator could be an investor who predicts that oil prices will rise, thus she buys (long position) oil futures contracts. Though not originally considered as main participants in derivatives markets, they provide liquidity enabling markets to function better. On the other hand their speculation activities can disrupt market performance and lead to high price volatility and bubbles, thus policy makers and regulators in many exchange markets constrain speculative actions. Speculators can further divided into scalpers, day traders and position traders considering the time duration of their strategies. Scalpers act within minutes trying to profit from minor price changes. Day traders close out their strategies within one trading day. Position traders expand their trading throughout considerable time periods, trying to forecast major price changes.

Arbitrageurs participate in the markets seeking for opportunities of riskless profits. Once such opportunity is spotted, arbitrageurs enter into two or more transactions in different markets. A typical example could be a trader who detects that a particular oil futures contract is overpriced considering the oil spot price at the time. Thus, she can sell the futures contract and buy oil barrels. Oversimplifying the procedure and ignoring price fluctuation and interest rates, once the contract expires she delivers the oil barrels to the buyer of the contract and she profits the difference of futures price minus spot price. However, such situations do not last long to be exploited. Supply and demand forces will reset the futures contract to its fair price. Pricing formulas of derivatives heavily relies on the non-arbitrage argument.

Lastly, it is noteworthy that stakeholders of commodities underlying derivatives can act as invisible analysts, though they do not use derivative markets for direct trading. Observing market movements and patterns, they make decisions on production and storage. According to Black (1976), through this category, although it does not contribute directly to the markets, derivatives offer their greatest benefit to the overall economy.

1.1.4 Forward and Futures Contracts

Despite their distinctive differences analyzed below, forwards and futures contracts are presented together as they share several common features.

1.1.4.1 Forward Contracts

A forward contract is an agreement between two participants, one of them in the long position (buyer) and the other one in the short position (seller), for the sale of an asset in a prearranged price, at a specific future date. The prearranged price, called delivery price and the specific date of delivery, called maturity date are decided when the contract is given birth, while the transaction takes place when the contract matures. Thus, no financial or asset flow happens when the contract is initially defined. It can be considered the exact opposite of a spot deal in which the asset is sold immediately. Forward contracts are generally traded on OTC markets and are highly customized to fulfill the needs of the two counterparties. Generally the two participants discuss privately and agree to the terms of the contract. Afterwards, the contract can be cleared either bilaterally or through the CCP.

The payoff of the long position of a forward contract is equal to S_T-F, where S_T is the spot price of the underlying asset when the contract matures and F is the delivery price written on the contract. If the spot price of the asset at delivery date is higher than the delivery price, the buyer profits their difference, as she buys an asset worth S_T for a lower price F. In the opposite case, if the spot price of the asset is lower, the buyer loses the difference between the two prices.

On the other hand, the payoff of the short position of a forward contract is equal to F-S_T, anti-symmetric to the payoff of the long position and in compliance with the zero sum game concept of derivatives; the profit (loss) of the buyer equals the loss (profit) of the seller and contract payoff sums to zero. Figure 1 illustrates the payoffs of a forward contract both for the buyer and seller of the contract.

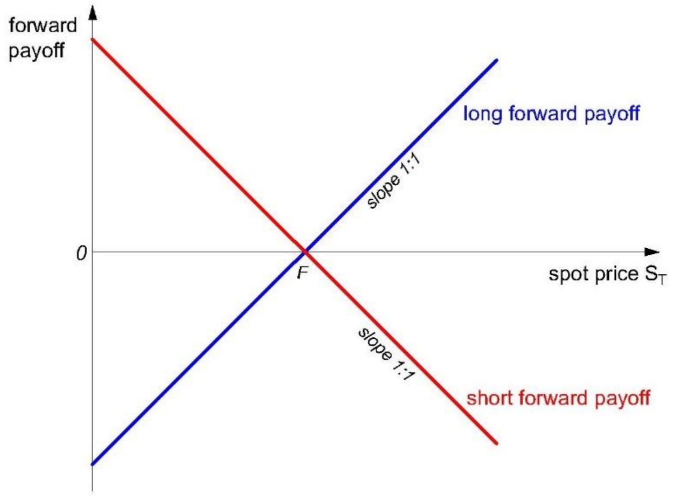


Figure 1. Payoffs for the long and short position of a forward contract.

1.1.4.2 Futures Contracts

A futures contract resembles a forward contract conceptually, but it is highly standardized and it is generally traded on an exchange market. The two counterparties match up through the clearing house of the exchange. The current futures price is the price in which the transaction will take place and it is determined by supply and demand of the specific futures. There may be multiple delivery dates throughout the year, usually every two or three months. Each futures is named conveniently after its delivery month.

Various specifications are standardized in futures. Firstly, the quality of the underlying asset must be designated and leave no ambiguity, such as in the case of agricultural futures in which a wide range of grades exist for the underlying assets. Secondly, the size of the contract is also defined, i.e. the quantity of the asset delivered per contract. When the underlying asset of the futures is not transferable, typical examples being the stock index and weather futures, the contract is settled in cash. Thirdly, delivery details must be also arranged. Generally, the delivery period spreads for the whole expiration month. Lastly, the place of delivery should also be prearranged if considerable transportation costs occur.

1.1.4.2.1 Margins and daily settlements

An important difference between forwards and futures is that the former settle only once, at maturity date, while the latter settle daily. As Hull (2018, p.53) outlines *''a futures is in effect closed out and rewritten at a new price each day''*. The new price is determined by supply and demand of the particular futures. This daily settlement, also known as *mark to market* procedure, occurs as an assurance against default risks. A futures contract between two investors consists technically of two separate futures each of which involving the clearing house and one of the two investors. The clearing house requires from the investors to have a margin account and deposit an initial fee named *initial margin*. In the end of every trading day, the futures resets its price and the difference is reflected in the investors' margin accounts, either as profit or loss, considering the investors' positions. A buyer of a futures profits when the asset price increases, while a writer profits when the asset price decreases. Some exchanges restrict the futures daily price movement by implementing a limit up and a limit down. If, after a daily settlement, a margin account falls below a certain threshold known as *maintenance margin*, the investor receives a *margin call* and she is obliged to deposit additional funds known as *variation margin*. The maintenance margin is usually equal to about 75% of the initial margin. Initial margin is not fixed; it normally varies between five and ten percent of the contract nominal value, justifying the label of futures as leveraged instrument, but it also depends on the type and credibility of the trader, as well as, the volatility of the market and the underlying asset. (Hull, 2018).

It is noted that in the case of standard forward contracts traded on OTC markets through CCP, a similar daily settlement procedure occurs in years after the crisis of 2007. Although forwards are not rewritten as futures do, daily margin payments following asset price changes are made to mitigate default risks. But even for forwards not cleared through the CCP, BCBS-IOSCO regulations have enforced initial and variation margins since 2015, though some exceptions apply (Kosowski and Neftci, 2015). ISDA master agreements usually used for bilaterally cleared forwards are associated by credit support annexes (CSAs) requiring daily revaluation of the contracts and the provision of daily collateral (Hull, 2018). Hence, it is obvious that contract default risks have been an issue for OTC markets and there is effort by market makers to implement stricter regulations.

1.1.4.2.2 The basis

During the life of a futures and before its maturity date, the futures price F_t at time t and the corresponding spot price S_t normally differ. The difference $B_t=F_t-S_t$ is the *basis* of the contract. As the futures contract is settled daily and the maturity date approaches, the two prices converge. Theoretically, at maturity date T, the two prices must be equal and the basis $B_T=F_T-S_T$ must be zero. Figure 2 illustrates the relationship of futures and spot prices.

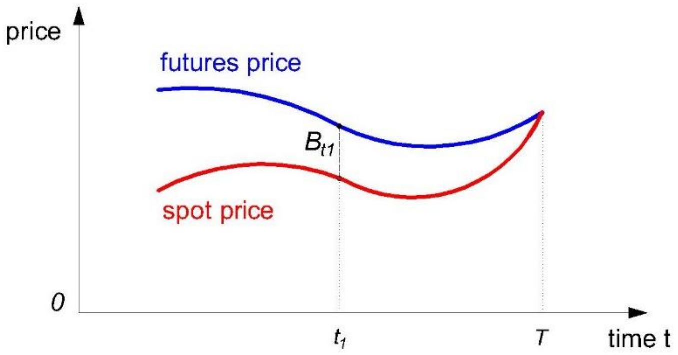


Figure 2. The relationship between futures and spot prices (basis).

The premise is grounded on the non-arbitrage argument which is usually deployed in the derivatives theory. If futures price is higher than spot price at delivery date, arbitrage can be achieved by selling a futures, buying the underlying asset in spot market and delivering the asset. If futures price is lower than spot price at delivery date, an arbitrageur can buy a futures, receive the asset and then sell it in the spot market. In both cases, supply and demand law will force the two prices to equalize and arbitrage opportunities will vanish. Practically, there are some costs associated with arbitrage and small differences between prices cannot be really exploited, hence there may be slight deviations from equilibrium $B_T=0$. Also, as expiration date approaches, futures volatility increases under what is known as Samuelson hypothesis or maturity effect, as futures contracts tend to be more sensitive to news during the last stage of their life (Samuelson, 1965).

1.1.4.2.3 Closing out

Practically, futures delivery rarely takes place. Most of investors involved in futures contracts prefer to close out their position before contract expiration. They can do so by entering a new contract of exactly the same type and opposing their original position. An investor in a long position closes out by selling a new contract, while an investor in a short position closes out by buying a new contract. Hence, the two contracts nullify each other. The ability of an investor to close out her position means that delivery does not necessarily taken by her. She may as well have closed out her position by entering a contract with another investor who has also closed out her position and so on.

1.1.4.3 Forward and Futures Contracts Differences

In the aggregate, forward and futures contracts display the following differences:

- A forward is traded on OTC markets, either bilaterally or through CCP. The two parties know each other and negotiate for the contract. A futures is traded in exchanges through the clearing house. The two parties usually do not know each other.
- A forward has usually one specific expiration date, while a certain type of futures offers various expiration dates.
- A forward is settled once, at the expiration date, while a futures is settled and rewritten daily. Recent regulations have partially smoothed out this difference as explained previously.
- In the case of forwards, the delivery of the asset is usually realized, while in the case of futures positions are closed out before expiration more often than not. Also, forwards are difficult to be sold to a third party, while futures are conveniently traded.

1.1.4.4 Forward and Futures Prices

The determination of forward and futures prices is based on non-arbitrage arguments and it can be summarized in the *cost of carry model*, firstly introduced by Keldor (1939). The model indicates the relationship between current forward/futures price and current spot price. It should be noted that despite their differences, forward and futures prices are considered to be equal in theory, though in practice there are some deviations due to futures daily settlements. For convenience, forward contracts will be examined in this work.

The cost of carry equation is expressed as:

$$F_0=S_0e^{cT} \qquad \text{(eq. 1.1)}$$

where F_0 is the current forward price, S_0 is the current spot price, c is the cost of carry and T is the remaining time until the contract matures.

The cost of carry c is a factor which summarizes income lost and earned on the asset. Intuitively speaking, it penalizes or rewards (or both) the investor for not buying or selling the asset at the spot but waiting for a future transaction. These ‘’penalties’’ and ‘’rewards’’ depend on the underlying asset. In case F_0 deviates from this relationship, arbitrage opportunities surface and supply and demand will bring it back to its fair value. Regarding the underlying asset and how it modifies the basic model, the most common cases are presented below:

a) In the simplest case in which the underlying asset earns no income, such as a stock which pays no dividends and a zero coupon bond, eq. 1 becomes:

$$F_0=S_0e^{rT} \qquad \text{(eq. 1.2)}$$

where cost of carry c equals the risk free interest rate r. The non-arbitrage argument is illustrated in this simple form. In case the forward contract is negotiated at price $F'_0>F_0$ or $F'_0<F_0$, an arbitrageur can implement the following strategies to achieve riskless profits:

<u>At time t=0 (current date)</u>

$F'_0>F_0$	$F'_0<F_0$
● Borrows S_0, for time T, at interest rate r	● Shorts the asset for S_0
● Buys the asset for S_0	● Loans out S_0 for time T, at interest rate r
● Shorts a forward contract for F'_0	● Stands long in a forward contract for F'_0

<u>At time t=T (maturity date)</u>

● Sells the asset for F'_0	● Gets the asset for F'_0

● Repays loan equal to S_0e^{rT}

● Return the asset

● Receives S_0e^{rT} from loan

† Profits made: $F'_0-S_0e^{rt} = F'_0-F_0$

† Profits made: $S_0e^{rt}-F'_0=F_0-F'_0$

Thus, equation 1.2 must be realized. Otherwise, an arbitrageur can profit without risks the difference $|F_0-S_0e^{rT}|$. For other assets examined below, similar arbitrage strategies can be deployed.

b) In case the underlying asset pays a known fixed income, such as a stock with known dividends, equation 1 becomes:

$F_0=(S_0–I)e^{rT}$ (eq. 1.3)

where I is the present value of the fixed income until the contract expires, and r is the risk free interest rate. In this case, the cost of carry includes both I and r.

c) In case the underlying asset pays a known yield, i.e. a known income dependent on the price of the asset, such as a stock index, equation 1 becomes:

$F_0=S_0e^{(r-q)T}$ (eq. 1.4)

where r is the risk free interest rate and q is the known yield of the asset. Obviously, in this case, c=r-q.

A subcase of assets with known yields is a forward contract on foreign currency exchange rates. Equation 1.4 becomes:

$F_0=S_0e^{(r-R)T}$ (eq. 1.5)

where r is the domestic risk free interest rate and R is the foreign risk free interest rate. Equation 1.5 is also known as *interest rate parity relationship*.

d) In this case the underlying asset brings in a known fixed loss. It is the opposite of the known fixed income case. A typical example is a contract on a commodity with storage costs. Equation 1.1 becomes:

$F_0=(S_0+U)e^{rT}$ (eq. 1.6)

where U is the cost of storage (or theoretically any fixed loss) and r is the risk free interest rate. If the cost of storage depends on the spot price of the asset, equation 1.6 becomes:

$F_0=S_0e^{(r+u)T}$ (eq. 1.7)

For this last case and in view of the non-arbitrage argument, a classification of the underlying assets should be made into investment assets and consumption assets. Investment assets are those which are held and traded primarily for investment purposes. Stocks and bonds are typical examples. Gold and silver are also investment assets despite the fact that they are also used for product manufacturing. On the other hand, consumption assets are held primarily for consumption purposes. Copper and oil are typical examples of consumption assets. The distinctive difference between the two classes is that, for investment assets, investors do not care if they hold the asset or a contract on the asset. However, they do care in the case of consumption assets. For a manufacturer, a ton of copper which can be used in a production process is more valuable than a contract on the same amount of copper. Thus, the non-arbitrage argument applies when F_0 is higher than its fair value, but it does not apply if F_0 is lower than its fair value. The copper manufacturer will still not be interested in forwards even if they are in sale. She will prefer to hold the copper and not be involved in the arbitrage process (Hull, 2018). Hence, for consumption assets, cost of carry given by equation 1.1 becomes:

$F_0=S_0e^{(c-y)T}$ (eq. 1.8)

where y is the convenience yield of the asset, in other words the ‘’reward’’ from holding the asset per se.

In determining the prices through the cost of carry model the following assumptions are made:

- There are no trading costs.
- Investors can borrow and loan at the default-free interest rate.
- The same tax rate applies to all profits.
- Once an arbitrage opportunity is spotted it will be immediately exploited.
- Markets are efficient and there are no short selling restrictions and fees.
- All flows are continuously compounded.
- The interest rate is considered constant. This assumption is used for the argument that forwards and futures prices are the same and that daily settlements of futures can be neglected for price determination purposes.

However in practice, interest rates follow a stochastic process and if forward and futures prices were the same, arbitrage opportunities would exist. In fact, the higher the correlation between spot prices and interest rates, the bigger the difference between forward and futures prices (Cox et al., 1981).

1.1.4.5 Value of Forward and Futures Contracts

The value f of a forward contract is defined as:

$$f=(F_0-F)e^{-rT} \quad \text{(eq. 1.9)}$$

where F_0 is the current price of the forward, F is the delivery price, r is the risk free interest rate and T is the duration until contract expiration. The variables K, r and T are fixed. According to the cost of carry model, F_0 fluctuates as far as asset price S_0 fluctuates. The value of a forward contract is zero when the contract starts and it can be positive or negative afterwards.

The value of a futures contract resets to zero at the end of every trading day as part of the mark to market process. During the day, the value of the futures can be positive or negative. In fact, a futures and the corresponding forward contract have the same value until the futures resettles.

1.1.4.6 Expectation Hypothesis, Backwardation and Contango

Regarding the relationship between the current forward/futures price and the expected spot price, there are three theories available. Firstly, the expectation theory suggests that forward/futures price equals the expected spot price of maturity date, that is, $F_0=E(S_T)$. This hypothesis assumes that there are no uncertainties, or that investors are risk neutral. Secondly, backwardation theory suggests that there are uncertainties and hedgers supply the contracts, while speculators buy them. The latter should be compensated with a risk premium, thus they will accept a long position as far as the forward/futures price is below the expected spot price of maturity date. Thirdly, contango theory which can be considered as the opposite of the backwardation theory, suggests that hedgers stand on the long side of the contracts and speculators stand on the short side. Again, it is speculators that should be compensated with a risk premium, thus forward/futures prices should be higher than the expected spot prices (Bodie et al., 2018).

1.1.5 Options

An option contract, just as a forward or a futures contract, is an agreement between two counterparties for the future transaction of an asset in a prearranged price. One of the participants of the contract sells or writes the contract and the other one buys or holds the contract. The distinctive feature of an option is that the buyer has the right, but not the obligation, to proceed with the transaction. On the other hand, the writer has the obligation to honor the contract. As a compensation for her advantageous position, the buyer pays the writer a premium at the start of the contract.

1.1.5.1 Types of Options

There are two types of options. A call option gives its buyer the right to buy the underlying asset in a predetermined price, called the strike or exercise price K, at expiration date. The buyer will exercise the right to buy the asset only if the price of the asset exceeds the strike price of the call option. A put option gives its buyer the right to sell S the underlying asset in the strike price at the expiration date. The buyer will exercise the right to sell the asset only if the price of the asset is below the strike price of the put option. In both types of options, the writer receives the premium and has a passive role thereafter.

Options can further be classified in European options in which the transaction can take place only at maturity date and American options in which the transaction can take place at any time during the life of the contract.

Regarding the types of options and investors' positions, there are four possible combinations:

- To buy a call option (long call). The buyer of a call option predicts a bullish market.
- To sell a call option (short call). The writer of a call option predicts a slightly bearish market.

- To buy a put option (long put). The buyer of a put option predicts a bearish market.
- To sell a put option (short put). The writer of a put option predicts a slightly bullish market.

Profits of the four positions are illustrated in figures 3 and 4 below. For a call option, as long as the asset spot price is below the strike price K, the option is not exercised; the buyer of the contract has loss equal to the premium paid, while the writer gains that premium. As the spot price exceeds K, the buyer starts to gain at constant rate, while the writer losses the same amount. Whatever the case, the option complies with the zero sum game. It should be noted that potential gains for the buyer and losses for the writer are infinite.

For a put option, as long as the asset price remains above the strike price K, there is no interest in exercising the option. Loss and profit for the buyer and the writer respectively are equal to the premium. As the spot price moves below K, the buyer starts to gain the amount that the writer starts to lose. In put options potential gains and losses are finite and are maximized when the spot price becomes zero.

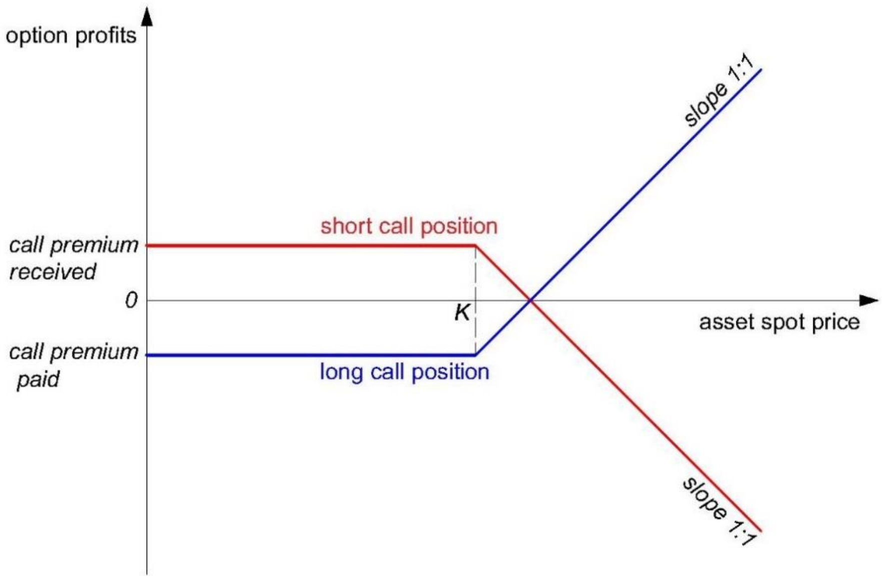


Figure 3. Profits of a long call (blue line) and the corresponding short call (red line).

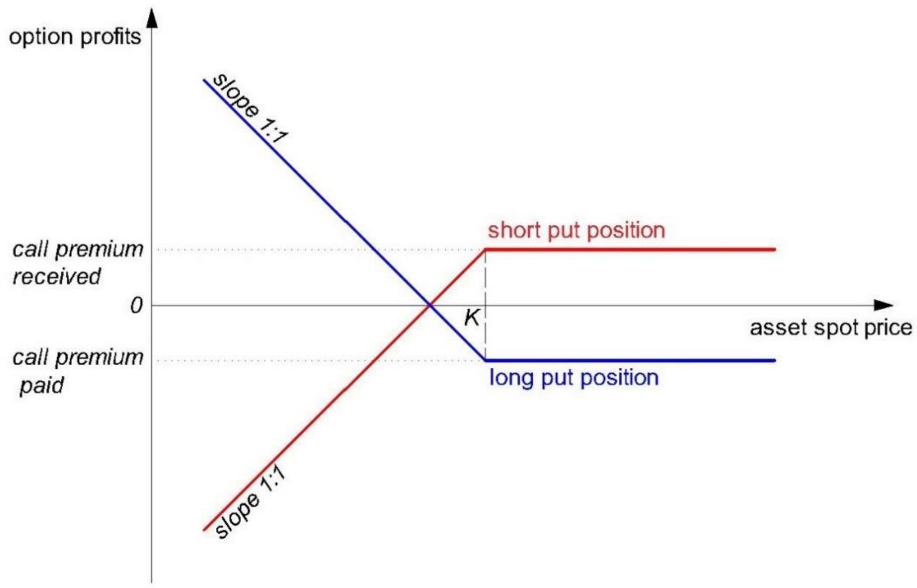


Figure 4. Profits of a long put (blue line) and the corresponding short put (red line).

Ignoring premiums, the payoffs of the four positions are the following:

Long call payoff: max(Spot price-K, 0)

Short call payoff: min(K-Spot price, 0)

Long put payoff: max(K-Spot price, 0)

Short put payoff: min(Spot price-K, 0)

At a specific time, if exercising the option delivers a positive payoff for the holder, the option is in-the-money. If exercising the option delivers zero payoff for the holder or in other words exercising is pointless, the option is out-of-the-money. In between the two cases, if the spot price equals the strike price, the option is at-the-money.

The intrinsic value of an option is the payoff that it would offer if exercised at the moment. Obviously, for in-the-money options intrinsic value is positive, while for out-of-the-money and at-the-money options intrinsic value is negative and zero respectively. However, even if intrinsic value is zero, the option is not worthless as it can move in the money at some point in the future. Thus, the option has a time value as well. The total value of the option is the sum of its intrinsic and its time value (Bodie et al., 2018).

1.1.5.2 Margins

Options are traded both in exchanges and OTC markets. As in the case of forwards and futures contracts, exchanges offer standardization and better mitigation of default risks, while OTC markets offer higher levels of customization. The Options Clearing Corporation (OCC), serving many markets, records all option transactions, intervenes between the two participants of the option and requires margins to be deposited in investors' accounts. The holder of an option holds a right, but not an obligation, hence a margin is not required from her. However, the holder is not allowed to buy on margin and leverage an option expiring in nine months or less. For long-term options, the buyer is allowed to borrow from her broker up to 25% of the position. On the other hand, the writer of an option holds an obligation. A margin is required from her, considering among other factors whether the option is naked or covered. Usually, the margin amount is equal to full premium received plus ten to twenty percent of the underlying asset (CBOE, 2000). As the asset spot price changes, a daily recalculation of the margin takes place and a margin call is also expected if necessary, just as in the futures markets, but without the daily settlement of the derivative.

1.1.5.3 Exercising and Closing Out

When an investor wants to exercise an option, the broker delivers an *exercise notice* to a writer of the option. The delivery takes place via the OCC. Through a standardized procedure determined beforehand, the OCC assigns the buyer to a specific writer. The open interest in the particular option is reduced by one.

The closing out process works as in futures trading. If a buyer of an option wants to withdraw, she can instruct her broker to sell an option of the same type. In the same way, a writer of an option can close out the position by buying the same option.

1.1.5.4 Option Prices and the Put-Call Parity Theorem

Option prices can be evaluated using once again the non-arbitrage argument. The option price is essentially the premium paid by the buyer of the contract. According to Bodie et al. (2018), the option price is affected by the underlying asset spot price and its volatility, the strike price, the maturity date, the risk free rate and any income or loss derived from the underlying asset. A difference in prices occurs between a European and an American option. Intuitively, as an American option offers more alternatives than a European option, for the former can be exercised at any point during the life of the option, the price of an American option has to be slightly higher than that of an equivalent European option.

An important equilibrium theorem in option valuation is the *put-call parity* relationship firstly introduced by Stoll (1969). It relates the prices of a European call and a European put option with the same strike price and expiration date. The general formula is given by:

$$c+Ke^{-rT}=p+S_0e^{yT} \quad \text{(eq. 1.10)}$$

In which, p is the price of the put option, c is the price of the call option, K is the strike price, S_0 is the underlying asset spot price, r is the risk free rate, T is the time duration until contract expiration and y is the yield depending on the underlying asset. For stocks paying no dividends, y=0, for stocks paying known dividends d, y=-d, for foreign currency paying a free interest rate equal to r_f, $y=-r_f$.

In its simplest form regarding assets with no income or cost, the put-call parity is given by:

$$c+Ke^{-rT}=p+S_0 \quad \text{(eq. 1.11)}$$

This form can be used to prove the put-call parity relationship under the non-arbitrage argument. Let two hypothetical portfolios A and B be constructed. Portfolio A consists of one stock and a put option. Portfolio B consists of a call option and a T-bond with face value equal to K and maturity date T, equal to that of the options. There are two scenarios at time T; stock spot price will be either higher than K or lower than K.

Portfolio A cost (t=0)	Portfolio B cost (t=0)
S_0+p	$c+Ke^{-rt}$
Portfolio A return (t=T)	Portfolio B return (t=T)
return=$S_T+(K-S_T)=K$, if $S_T<K$	return=$0+K=K$, if $S_T<K$
return=$S_T+0=S_T$, if $S_T>K$	return=$(S_T-K)+K=S_T$, if $S_T>K$

Under both scenarios, the returns of the two portfolios are identical. Hence their cost should be the same. Otherwise an arbitrageur could buy the cheap portfolio and sell the expensive one. The costs of the portfolios are the two sides of the equation 1.11. Similar non-arbitrage arguments can be deployed to the defense of the put-call parity regarding other underlying assets.

Relative premium is defined as the ratio of the premium value to the total value of the underlying asset that the option contract refers to. In the case of stocks, an option usually refers to a lot of 100 shares. Stoll (1969), using the put-call parity, indicated that the difference of relative call and put premiums approximately equals the risk free rate, that is:

$$\frac{c}{V} - \frac{p}{V} = r \qquad \text{(eq. 1.12)}$$

where c and p are the call and put premiums respectively, V is the total value of the underlying asset specified by the contract and r is the risk free rate.

It is noted that the put-call parity theorem applies only to European options. American option premiums cannot be strictly defined under this equilibrium, for they are allowed to be exercised at any point during the option life. Hull (2018) suggests the following lower and upper bounds for American options:

$$S_0e^{yT}-K \leq c-p \leq S_0-Ke^{-rT}$$

with variables defined as previously.

1.1.5.5 Trading Strategies with Options

Options have proven to be a versatile tool for investors. They can be combined with either other financial instruments or other options. Below, the most common strategies involving options are briefly analyzed.

1.1.5.5.1 Options combined with the underlying asset.

In this category there are four popular positions: the covered call, protective call, protective put and covered put. To acquire a covered call position, an investor has to write a call option and buy the underlying asset. It is the opposite of the naked option position in which the underlying asset is not owned by the writer. The profit pattern of a covered call is illustrated in figure 5. As it can be observed, the investor is "covered" by an increase in the asset spot price. However, she actually "loses" the premium, if the asset spot price drops significantly.

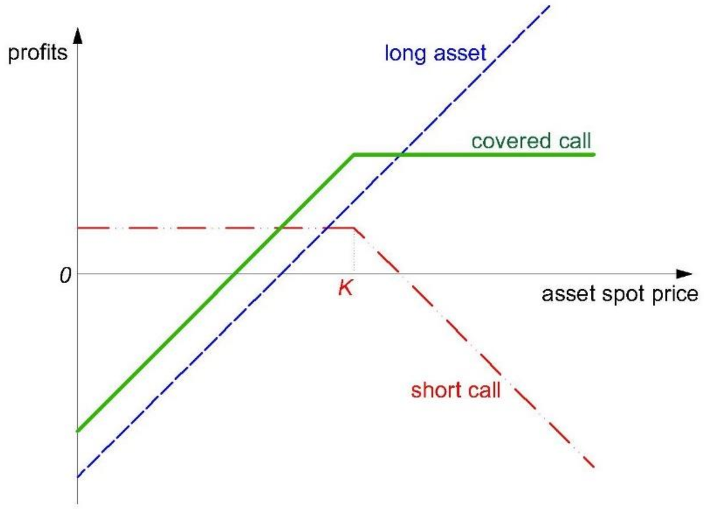


Figure 5. Covered call profit pattern.

The protective call, illustrated in figure 6, is the reverse of the covered call. The investor buys a call option and shorts the underlying asset. Hence, if the asset spot price increases, the losses are mitigated in exchange for lower profits due to premium in case spot price decreases.

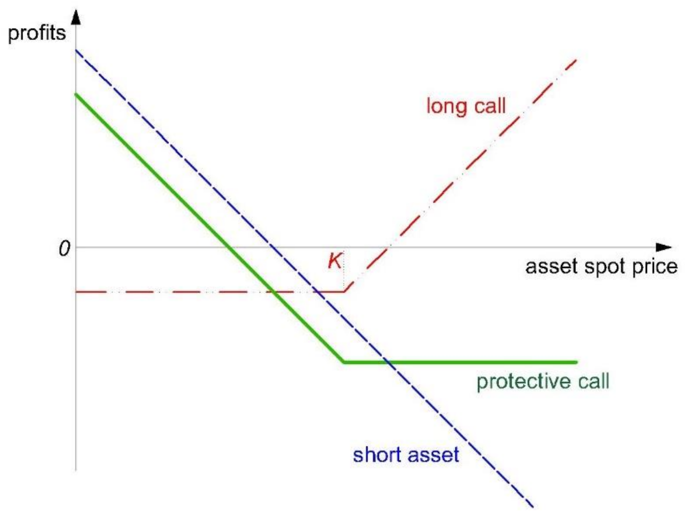


Figure 6. Protective call profit pattern.

The protective put consists of a put option and the underlying asset. The profit pattern is illustrated in figure 7. The investor is "protected" from a drop of the asset spot price. On the other hand, in case the asset spot price increases, the investor gains less than she would if she did not enter the put option contract.

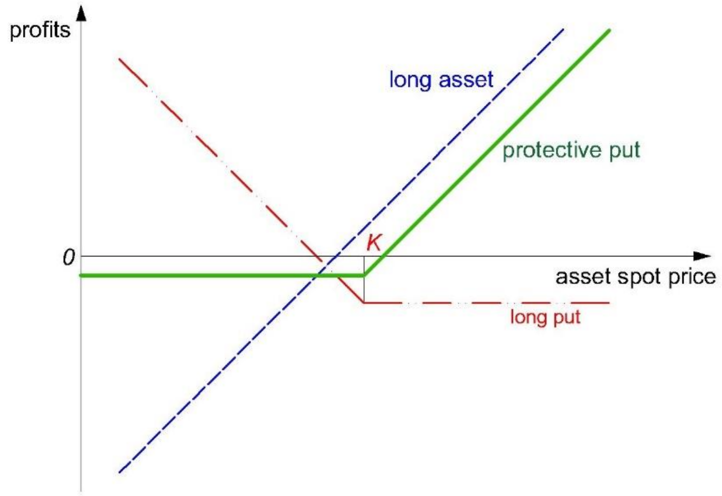


Figure 7. Protective put profit pattern.

The covered put, illustrated in figure 8, is the reverse of the protective put. The investor is "covered" if the spot price drops significantly, but in exchange she suffers losses if the spot price increases significantly.

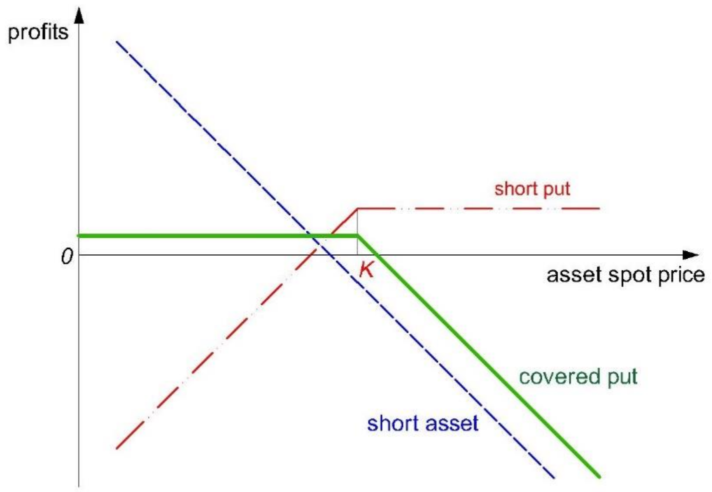


Figure 8. Covered put profit pattern.

1.1.5.5.2 Options combined with other options

Two types of position are favored by investors in this category, spreads and combinations.

A spread is achieved by taking a position in two or more calls, or, in two or more puts for the same asset. There are various spreads, considering the relative specifications of the options combined.

A bull spread consists of holding a call option with strike price K_1 and writing a call option with strike price $K_2>K_1$. Premium paid for the former option is always higher than premium received for the latter option, for $K_1<K_2$. Both options have the same maturity date. Figure 9 illustrates the profit pattern of a bull spread. The investor of this position predicts a bullish market and mitigates both her potential losses and profits. Bodie et al. (2018) argue that the investor taking a bull spread position may not think of a bullish market but of the one option being overpriced compared to the other.

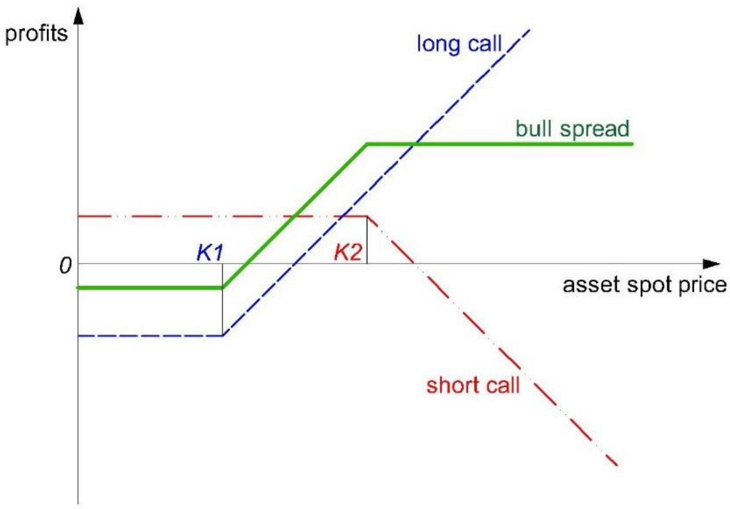


Figure 9. Bull spread profit pattern.

A bear spread consists of writing a put option with strike price K_1 and buying a put option with strike price $K_2>K_1$. Both options have the same maturity date. Figure 10 illustrates the profit pattern of a bear spread. The investor predicts a bearish market and, as in bull spreads, both potential losses and profits are mitigated.

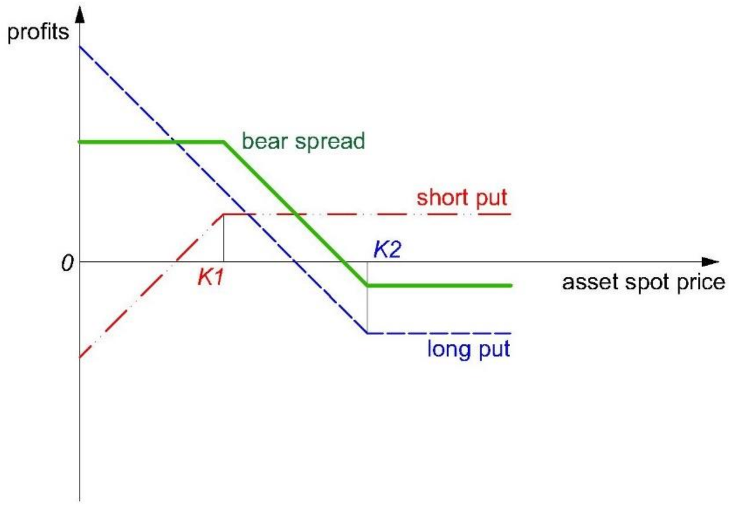


Figure 10. Bear spread profit pattern.

A somewhat more complicated spread is the butterfly spread. This position is achieved by buying a call option with strike price K_1, buying a call option with strike price K_3, and selling two call options with strike price $K_2=(K_1+K_3)/2$. The profit pattern is illustrated in figure 11. The position is hold by an investor who does not anticipate big market movements in either direction.

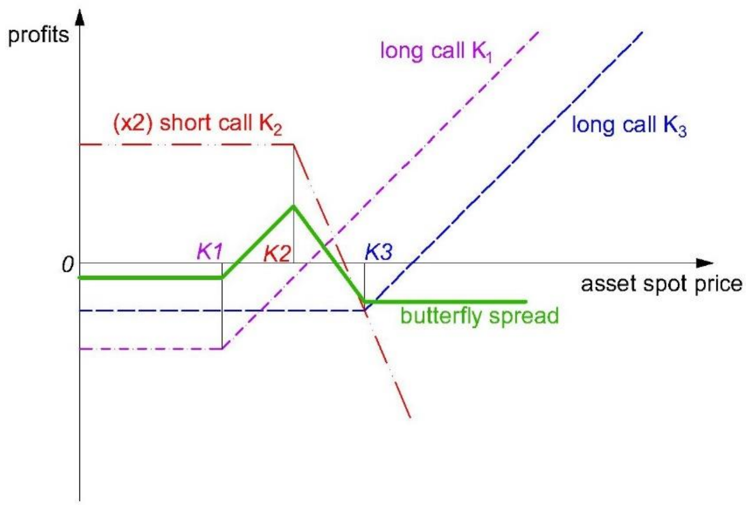


Figure 11. Butterfly spread profit pattern.

A calendar spread consists of selling a call option with strike price K and maturity T_1 and buying a call option with strike price K and maturity $T_2>T_1$. The profit pattern is illustrated in figure 12 and resembles that of the butterfly spread. The graph is presented at time T_1 when the short call position expires and assuming that the long call position is closed out.

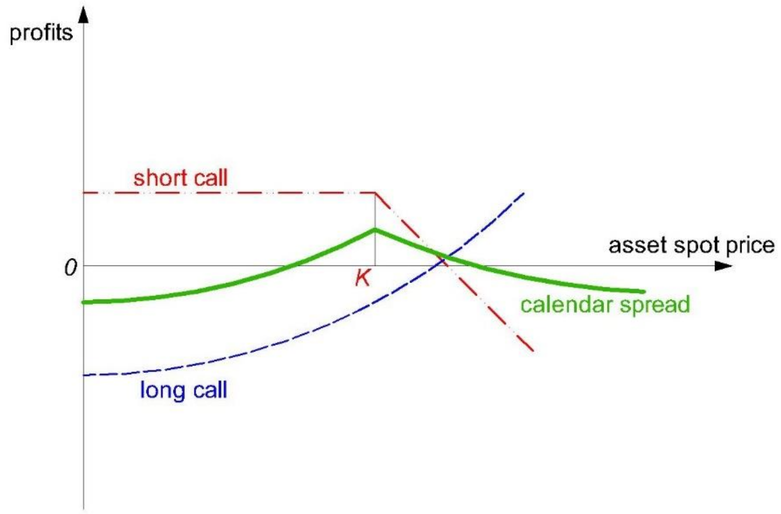


Figure 12. Calendar spread profit pattern.

A comprehensive list of spreads cannot be presented here. Profit patterns can be plenty combining different options. For example, diagonal spreads consist of options with different strike prices and different expiration dates. Even spreads can be combined with each other and produce further spreads, such as the box spread which is the result of a bull and a bear spread.

Combinations are investment strategies in which position is taken in both call and put options. A simple case of combination is the straddle. A straddle consists of holding a call and a put option with the same strike price and expiration date. The profit pattern is illustrated in figure 13. A trader investing in a straddle anticipates a big move of the price of the underlying asset, either upwards or downwards.

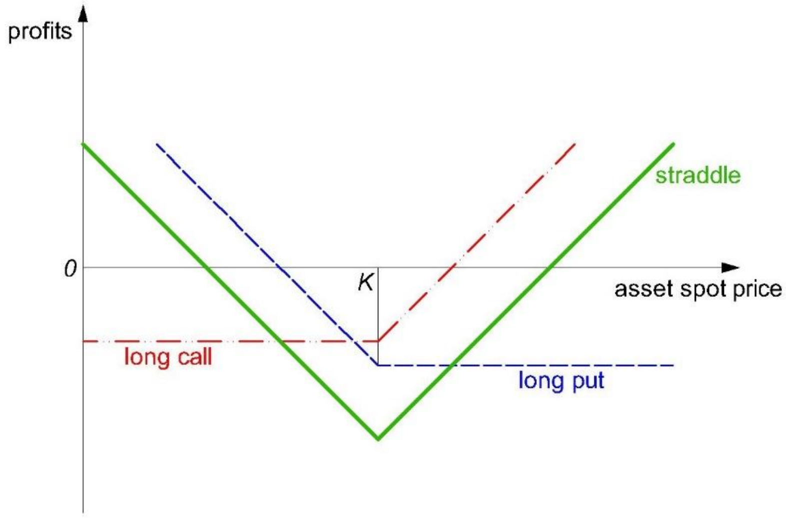


Figure 13. Straddle profit pattern.

A strip is created by holding one call and two puts, while a strap is created by holding two calls and one put. In both strips and straps, options used have the same strike price and expiration date. The profit patterns are illustrated in figures 14 and 15. In both cases, the investor anticipates a big move of the price of the underlying asset. A positive move slightly favors the strap strategy, while a negative move slightly favors the strip strategy.

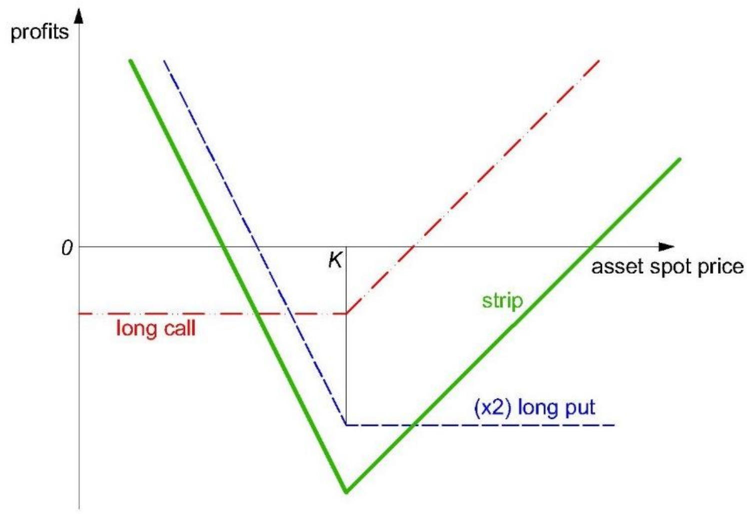


Figure 14. Strip profit pattern.

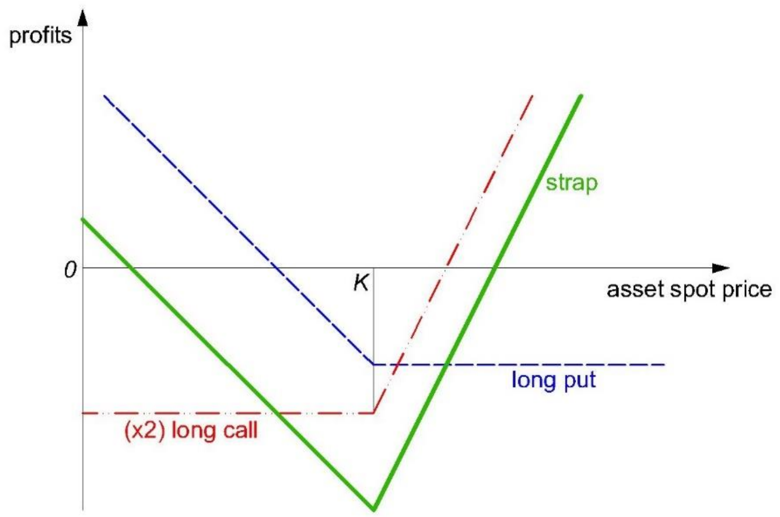


Figure 15. Strap profit pattern.

A strangle consists of holding a put with strike price K_1 and holding a call with strike price $K_2>K_1$. The profit pattern is illustrated in figure 16. The investor anticipates a big move of the underlying asset in either direction.

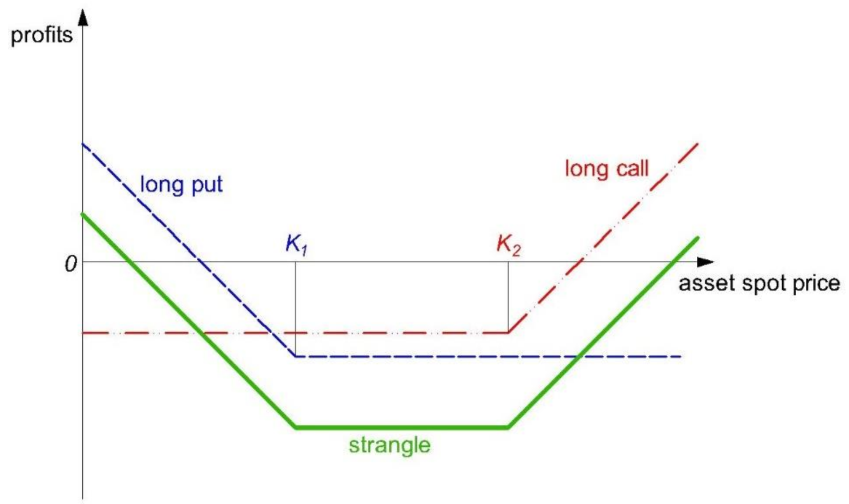


Figure 16. Strangle profit pattern.

1.1.5.6 Exotic Options

Exotic options differ from plain vanilla options in their structure and sometimes offer unique features. They essentially come from OTC-traded customized options that were successful enough to be standardized in either OTC markets or exchanges. There are a few reasons for their development and success. They usually offer higher profit margins than conventional options do. They can also prove a better hedging tool for specific companies or provide a way of maneuvering around accounting and tax regulations (Hull, 2018). Just a few of them are presented here.

An Asian option, with a name that has nothing to do with the geographic location in which it is traded, offers a payoff dependent on the average price of the underlying asset during the option life. A barrier option offers a payoff only if the asset price overcomes an upper or lower threshold. It can also immediately expire unexercised if the asset price goes below a lower threshold. Lookback options offer a payoff dependent on the peak and bottom of the asset price during the life of the option. Digital options may offer a pre-determined payoff relying on whether a specific condition about the asset price holds (Bodie et al., 2018).

1.1.6 Swaps

A swap is an agreement between two counterparties to exchange cash flows at regular time intervals for a certain time period. They can be considered as repetitive forwards, considering that forwards are essentially one-flow swaps; the participants of a forward exchange an asset that can potentially be immediately sold for its spot price creating a cash flow and a cash flow derived from the delivery price of the contract (Bodie et al., 2018). Swaps are traded on OTC markets. Like in futures trading, there is usually an intermediate player who stands between the two counterparties and shoulders the risks. The two counterparties may not know each other. Each one deals only with the intermediate player. The latter does not need to enter simultaneously into the contracts, as the needs of the two counterparties may not spawn at the same time. Hence, the intermediate player has the role of the market maker and provides liquidity.

1.1.6.1 Swap Mechanics

The interest rate swap is by far the most popular contract, hence it will be used for illustration of swap mechanics.

The most common interest rate swap is one in which fixed interest rate is exchanged for floating interest rate, usually proxied by LIBOR (London Interbank Offered Rate), that is the interest rate which a highly credible bank can borrow at. A swap agreement of this type requires that one of the participants want to dispose of a fixed interest rate income or liability for a LIBOR income or liability and that the other participant have the exactly opposite desire.

Theoretically, *the comparative argument* is deployed to justify a swap agreement. Let investors A and B want to borrow. Investor A has been assessed with higher credibility than investor B has, thus loaners offer lower interest rates, both fixed and floating, for A than they do for B. The assumed interest rates are presented in table 1.

Table 1. Fixed and floating interest rates for investors A and B.

	Fixed interest rate	Floating interest rate
Investor A	a	LIBOR+c
Investor B	b	LIBOR+d

According to the credibility premise made above, it follows that $a<b$ and $c<d$.

Let also be assumed that $b-a>d-c$. In other words, while investor A outperforms B in both markets, the difference is more obvious with regard to fixed interest rates. Under this assumption, investor A has a comparative advantage over investor B in the fixed interest rate market. Investor B comparative advantage is in the floating interest rate market. If both investors want to borrow in their corresponding non-advantageous interest rates, they can enter a swap agreement and achieve better rates than the ones offered to them. Assuming that an intermediary, such as a bank or other financial institution enters the agreement as well, the mechanism of figure 15 will take place.

Figure 17. The swap mechanism and flows.

The logical sequence of this swap can be analyzed as follows:

- Investor A wants to borrow at LIBOR+c, but her comparative advantage is in fixed rates market.
- Investor B wants to borrow at b, but her comparative advantage is in floating rates market.

- They both borrow in their advantageous markets (not what they really want).
- They enter their corresponding swaps with the intermediary. Let be assumed that intermediary charges x for compensation. That is the difference of bid and offer quotes. The rate flows of the swaps are shown in figure 15. Investor A ends up with LIBOR outflows and investor B with fixed outflows (what they really want).
- The rate profit for each investor, assuming they split profit in half, is: $p_A=p_B=\frac{(b-a)-(d-c)-x}{2}$
- The rate profit for the intermediary is obviously x. The sum profit is P = (b-a)-(d-c).
- Indeed, without a swap, investor A would pay LIBOR+c. Through the swap (see figure 15) she pays $a+LIBOR-(a-c-p_A)=LIBOR+c-p_A<LIBOR+c$.
- Without the swap, investor B would pay b. Through the swap she pays $LIBOR+d-LIBOR+(b-d-p_B)=b-p_B<b$.

1.1.6.2 Swap Value

The flows of an interest rate swap can be approached as they were bond payments. Specifically, for one of the participants, the flows are a combination of a long position in a hypothetical bond that pays fixed interest rate coupons and of a short position in a hypothetical bond that pays floating interest rate coupons. All payments refer to the principal amount of the swap. For the other participant the situation is reversed, so that the zero sum game concept is satisfied. Thus, for the first participant the value is:

$V_A=B_{fix}-B_{float}$

where V_A is the swap value from the perspective of the first participant and B_{fix} and B_{float} are the respective payments of the hypothetical bonds, normally discounted with the present value principles.

For the second participant the value is:

$V_B=B_{float}-B_{fix}$

Obviously, $Sum=V_A+V_B=0$.

When the swap agreement is initiated, its value is zero. It can be either positive or negative afterwards, considering the participant in question.

1.1.6.3 Types of Swaps

As mentioned previously the fixed for floating interest rate swap is the most popular of interest rate swaps.

According to Hull (2018), other commonly used swaps are:

- The *fixed for fixed currency swap* in which the fixed interest rates in two currencies are exchanged. Each currency pays on each own principal.
- The *fixed for floating currency swap* in which the fixed interest rate in one currency is exchanged for the floating interest rate in another currency. Again, each currency pays on each own principal.
- The *floating for floating currency swap* in which the floating interest rates in two currencies are exchanged, with each currency paying on each own principal.
- The *quanto swap* in which interest rates of two currencies are exchanged, with each currency paying on the same principal enumerated in one of the two currencies units.
- The *equity swap* in which an interest rate is exchanged for the yield of an equity index.

Generally, swaps can offer a high level of flexibility. For example, the commercial paper (uncollateralized short-term firm bonds) rate instead of LIBOR can be used as a proxy for floating interest rate. Also, the principal may not be constant but decline in time in amortizing swaps. In forward swaps exchanges do not happen before a predetermined time point. In compounding swaps flows are postponed and compounded until the expiration date. In extendable swaps one of the participants can opt for extension of the expiration date of the swap. Contrariwise, in puttable swaps, early abortion is possible. In swaptions, the buyer have the right to enter a pre-determined swap at some point in the future (Hull, 2018).

1.2 FUTURES AND SPOT PRICES CAUSALITY

Before proceeding to futures and spot prices causality theory per se, price discovery and market efficiency are presented as they are tightly associated with the concept of causality between markets.

1.2.1 Price Discovery

Price discovery is the process through which the efficient equilibrium price of an asset is determined in a marketplace. It is considered one of the main functions of markets, as buyers and sellers gather and ‘’agree’’ on a specific trading price. Regarding financial markets, price discovery should not be confused with valuation; the former refers to the spot price of an asset while the latter is the ‘’fair’’ present value of an asset derived from a theoretical model. Metaphorically speaking, price discovery is the road through which an asset reaches its intrinsic value. The less obstacles or ‘’friction’’ on the road, the closer the asset will get to its ‘’pricing destination’’. Gupta et al. (2018) distinguish between long-term (static) price discovery which is the very presence of an equilibrium price and short-term (dynamic) price discovery which depicts how a new set of information is incorporated into and transmitted through markets. Price discovery mechanism is obviously built on supply and demand principle foundations. Other factors that hamper or facilitate the process attach to this framework; internally, trading volume and liquidity, market design and microstructure, and externally, macroeconomic and geopolitical variables can influence price discovery.

According to Schreiber and Schwartz (1986), the market architecture features which may have an impact on price discovery are:

a) Market makers role. Whether the market makers accept a passive role by providing just liquidity to the market or operate more actively by manipulating spreads for inventory control purposes or by counterbalancing price volatility will affect the price discovery process.

b) Call market and continuous trading system. It is not clear whether the execution of orders in lots within specific trading sessions or the regular execution once opposite orders cross each other is beneficial for the price discovery process.

c) Effective information systems in terms of the transmission speed of news, transaction prices, quotations and volumes.

d) Order priority rules and the gathering of orders in limit books and of public on the trading floor promote price discovery.

In case there are two (or more) markets for an asset to be traded on, price discovery happens in both markets and it depends on communication costs and the interdependencies of those markets. If costs are above a certain high threshold, the markets are independent and asset price follows its own pathway for each market, while if costs are eliminated, the markets are considered as completely integrated. In the most realistic scenario, markets will be partially integrated and some kind of relationship will exist between the prices of the asset. Price differences will be subject to arbitrage opportunities and its speed of implementation which in turn will depend on market regulations and policies and trading costs. According to Garbade and Silber (1979), if price difference exists between two partially integrated markets X and Y, either price of market X moves to price of market Y and vice versa with both prices moving symmetrically in terms of speed, or only market X adjusts its price towards price of market Y. In the latter case, market Y is the ‘’dominant’’ market and market X is its pure ‘’satellite’’. Of course this relationship may move within a spectrum in which the roles of ‘’leader’’ and ‘’follower’’ are not so clearly defined.

When markets compete for the price discovery process of an asset, under the trading cost hypothesis, the market with the lowest trading costs will absorb new information faster and will dominate the price discovery process. Trading costs include bid-ask spreads, commission fees and the potential intangible cost of market impact (Fleming et al., 1996). Investor structure can also affect price discovery process. Bohl et al. (2011) found that markets with higher percentage of institutional investors than the percentage of individual investors dominate price discovery, as the former tend to be more informed, sophisticated and trade rationally, while the latter are prone to behavioral biases and sentiment.

Closely related to price discovery, pricing efficiency refers to how close the actual price of an asset is to its intrinsic value. Implicitly, it measures the success of price discovery mechanism. More precisely, in practice, the observed price P_t of an asset will equal its fundamental value P^*_t plus a stochastic noise e_t, that is:

$P_t = P^*_t + e_t$

Black (1986) defined the pricing efficiency ratio as $ER = P^*_t / P_t$ which in a pricing efficient market should equal 1. If ER>1, the asset is undervalued, while if ER<1, the asset is overvalued. A problem lies however in setting the intrinsic value and particularly in the correct values that should be used for the variables of holding period, discount interest rates and accrued profits/losses of a potential model (Ayadi, 1994). The issue of a suitable comparison for observed prices is also highlighted by Schreiber and Schwartz (1986) as the most significant reason for which price discovery is neglected by investors.

1.2.2 Market Efficiency

Since its theoretical birth, efficient market hypothesis (EMH) has been a controversial topic for economists. Bachelier (1900) started, unbeknown to him, the spark which led to EMH over half a century later. His dissertation concluded that speculators should expect no returns in the financial markets, or in other words, financial markets offer speculators a ‘’fair game’’.

Kendall and Hill (1953) found that the set of price time series they examined could not produce a clear pattern, apart from superficial cycles, and that changes in prices seemed to move randomly, or in other words follow a Brownian motion. The random walk model was embraced by Fama (1965) who discarded the ‘’chartist’’ approach as valueless and gave birth to EMH. According to EMH all available information is already integrated into the market prices and any new piece of information will be instantaneously and rationally absorbed. Thus, there can be no undervalued or overvalued assets, and investors, either sophisticated or uninformed ones, cannot outperform the market or earn a higher than average return consistently and without taking extra risk. The EMH is based on three ‘’sufficient but not necessary’’ assumptions regarding financial markets (Fama, 1970):

- There are no trading costs.
- All information is available to all investors at no cost.
- Investors have homogeneous expectations and their rationality will result to the same interpretation of information.

It is clear that hindrance of EMH can be either due to trading and trading mechanism or due to human factor in perception and decision making-or both.

Fama (1970) classified EMH into three categories. All three categories presume the fact that prices reflect all available information. Their difference lies on the set of that information;

- The *weak form* of EMH in which prices incorporate all information which can be excavated by examination of past prices.
- The *semi-strong* form of EMH in which prices incorporate not only information about past prices, but also publicly accessible information about a firm's management, organization and practices.
- The *strong form* of EMH in which prices reflect the set of information of the previous two forms plus intelligence from business insiders.

In case strong form holds, weak and semi-strong forms also hold. In case weak form does not hold, semi-strong and strong forms do not hold.

EMH challenges some basic concepts in finance. In its weak form it defies technical analysts while in its semi-strong form it nullifies both technical and fundamental analysis. Thus, it questions the very existence of fund managers (unless they can secure private information) and actively traded portfolios and implicitly suggests that passively investing in a market index is the optimal approach. And indeed, very few professionally managed active funds have achieved to beat the market index (Malkiel et al., 2005). But if markets are efficient, then there is no point in acquiring and analyzing new information and this will result in market inefficiency. The theoretical absurd conclusion is that there could be a threshold of market efficiency level beyond which trading would have no meaning and markets would eventually shatter. Ironically, it is the belief of -at least- some investors that markets are inefficient that keeps markets efficient. Grossman and Stiglitz (1980) argue that costless information should be a necessary assumption, not a sufficient one. In practice, information, outlined by many as the most precious commodity in markets, costs, and investors seeking for it should be rewarded with excess returns, thus markets cannot be efficient.

A main argument of adversaries of EMH is that, if markets are efficient, price anomalies should not exist. The inspection of a price anomaly could lead to two outcomes; in the first outcome, the anomaly is just a statistically random deviation and of no concern and in the second outcome, the anomaly is the result of market inefficiency or flawed pricing models. Many anomalies of the past have been eliminated or minimized when they became well known through academic research. For example, the weekend effect and January effect have been arbitraged away leading to more efficient markets (Schwert, 2003). If this is the case however, it means that markets were once inefficient regarding a specific anomaly, thus anomalies can undermine EMH. On the other hand, the value effect and size effect anomalies which have also almost disappeared, were attributed to inadequacy of CAPM. Suitability of pricing models also concerned Fama (1991) who revisits his previous work and rejects much of the research done for testing EMH until then, arguing that it is *jointly* EMH *and* the underlying corresponding asset pricing model that is tested by researchers and not EMH solely.

But some price anomalies, even after their discovery, are persistent. Lo (2007) distinguishes between ‘’academic’’ and ‘’realistic’’ anomalies. If limits to arbitrage, such as implementation costs, taxes, market structure, illiquidity and institutional stiffness, prevent investors from capitalizing on observed anomalies, there is no economic value in them and thus no action will be taken to mitigate mispricing. It should be noted that Fama (1965) even loosely, distinguishes between theory and practice in EMH from the very beginning, mentioning that practically some dependence in random walk model is acceptable, depending on the context.

The emerging field of behavioral finance challenges EMH even further. Human decision making is subject to cognitive and psychological bias and humans cannot act fully rationally under uncertainty, thus the foundations of market efficiency are undermined. The existence of some anomalies and their persistence may be attributed to behaviorism. Prospect theory suggests that the expectation of loss results in greater amount of disappointment than the amount of pleasure that the equivalent expectation of gain results to, and challenges the traditional utility theory (Kahneman and Tversky, 1979). In view of over-reaction constituting behaviorism and thus market inefficiency, Fama (1998) disagrees by arguing that this phenomenon has equal chances of happening as under-reaction, hence it complies with EMH. Proponents of EMH accept the existence of bias decision making, but they argue that arbitrageurs outcompete noise traders and reverse prices to their intrinsic values.

However, Malkiel (2003) attempts to reconcile the two sides by essentially splitting EMH in its theoretical and practical parts; while mispricing is evidence of inefficiency and in many cases the apparent result of investors' behaviorism, it is not a sufficient condition of rejection of EMH. It requires a trading strategy which can exploit that inefficiency. Mispricing anomalies, such as short momentums or seasonal movements cannot be truly abused if trading costs cannot be overcome. Bubbles, a strong argumentative ram of market inefficiency advocates, also cannot be mined ex-ante, without heavy risk acceptance; a bubble is not obvious during its bloom and, even if it is recognized, its unknown potential duration does not allow for a light-hearted investing decision. Furthermore, market crashes, such as that of 1987, involve a combination of macroeconomic and political events which reshape investors' rationale.

A step further, Lo (2004) suggested an updated version of EMH, the adaptive market hypothesis (AMH), wedding components of original market efficiency and biologically driven factors. Rationality, induced by profit maximization and utility theory, is partially substituted by the evolutionary biology doctrine. Decision making involves finite rationality which enables for finite optimization under the traditional economic principles, but it also involves a biological dynamic heuristic process which forces investors to seek for satisfaction and is completely unrelated with economics. The market which is considered static in EMH (albeit Fama (1965) explicitly acknowledges the dynamic nature of markets) compares with a dynamic ecosystem and behaviorally homogeneous investors compare with a species. Any change in the system affects the heuristic process of the species. Behavioral traits such as fear, greed and overconfidence are just elements of this process which enables for satisfaction. Thus, prices reflect information which are interpreted both rationally and emotionally. Contrary to EMH, arbitrage opportunities are allowable in AMH occasionally and investment strategies are time-regime dependent.

The empirical research testing for EMH in various markets is vast and out of the scope of this work. Ostensibly, in a survey of finance professors-viewed as specialists in the subject-, Doran et al. (2010) found that the majority of them consider markets standing between weak and semi-strong form efficiency and that two out of three professors hold passive portfolios. In apparent self-contradiction however, overconfidence to outperform the market is a critical factor in their trading, regardless of their opinion about market efficiency levels. But there is still no scientific consensus about markets efficiency. Lo (2007) mentions that the paradigm of EMH is too abstract and theoretical to be tested empirically and even if it would be constrained within a certain framework, the result would be a meaningless investigation of joint hypotheses. Alternatively, he suggests that *relative market efficiency* would offer more realistic and tangible conclusions. Thus the examination of a market would result not in absolute acceptance or rejection of its efficiency, but in an ''efficient rating'' when compared with another market.

1.2.3 Interrelations between Futures and Spot Markets

Futures and spot markets are connected through the underlying assets, hence interrelationships exist regarding their prices and returns. Interdependencies between the two types of markets can be used to assess the market efficiency and price discovery concepts, at least relatively. Below, relationships between current futures prices and expected spot prices and between current futures prices and current spot prices are used as the foundations for the examination of those interdependencies.

Before moving on, the importance of futures markets for risk management purposes should be highlighted. Performance of futures markets as risk management tools is considered as a success indicator for their very existence (Garbade and Silber, 1983). Black (1986) mentions spot price volatility and futures contracts risk transfer capability among the success factors for futures contracts endurance in time. Brorsen and Fofana (2001) also notice active and volatile spot markets as a necessary condition for the existence of a corresponding futures market. Hence, the need for hedging seriously determines the success of futures markets. Potential relationships and interdependencies between futures and spot markets are researched in view of futures markets as suitable risk management tools.

1.2.3.1 Current Futures Price and Expected future Spot Price

Current futures price and the expected spot price when the futures contract matures is based on the expectation hypothesis, also known as unbiasedness hypothesis. According to that, futures price F_t should be an efficient and unbiased estimator of future spot price S_T, that is:

$E(S_T|I_t)= F_t$

where t is current time, I_t is available information at time t and T is the futures maturity date. Two equivalent for this purpose models can be used for the investigation of the expectation hypothesis; the risk premium model and the asset pricing model.

The risk premium model states that:

$$F_t=E(S_T)e^{-p(T-t)} \quad \text{(eq. 2.1)}$$

where p is the risk premium of the underlying asset.

Simplifying for time differences and allowing for rational innovations, equation 2.1 can be restated in logarithmic form as:

$$\log S_t=\alpha+\beta \log F_{t-1}+u_t \quad \text{(eq. 2.2)}$$

The asset pricing theory of Fama (1970) states that:

$$E(S_T|I_t)=\beta F_t+\alpha(r_M-r_F)S_t+e_t \quad \text{(eq. 2.3)}$$

where r_M is the risk-adjusted interest rate and r_F is the risk free interest rate, hence r_M-r_F is the risk premium. For both equations 2.2 and 2.3, coefficient β is associated with informational efficiency and price discovery, while coefficient α is associated with risk premium and the risk management function of futures. If market efficiency is to hold, $\beta=1$ should also hold. If the expectation hypothesis is to hold $\alpha=0$ and $\beta=1$ jointly should also hold. There are three possible deviations from the latter joint hypothesis: If $\alpha\neq0$ and $\beta\neq1$ there is evidence of market inefficiency. If $\alpha\neq0$ and $\beta=1$, there is a constant risk premium which forces futures prices to be biased. If $\alpha=0$ and $\beta\neq1$, there is a time-varying risk premium that forbids futures prices from being unbiased (Ankamah-Yeboah et al., 2017).

However, Chen and Zheng (2008) argue that futures cannot be an unbiased predictor of the future spot price at all. Unbiasedness would imply either that investors are risk neutral and they do not require compensation for extra risk or that the futures does not carry any systematic risk. They also argue against research conducted on the investigation of the relationship between current futures price and the expected spot price for market informational efficiency purposes. The latter can be only examined through the investigation of $e_t=F_t-F_{t-1}$ and whether e_t follows a martingale sequence and is in accordance with the concept of market efficiency as this was originally defined by

Fama (1970). Gupta et al. (2018) also state that the unbiasedness hypothesis requires both market efficiency *and* risk neutrality and that is rarely the case in real markets. Arouri et al. (2012) and Jena et al (2019) argue that when β deviates from its equilibrium value of unity, a lead-lag relationship occurs between the markets and arbitrage opportunities arise. This lead-lag relationship is related to informational dynamics, markets relative efficiency and price discovery and it is investigated through causality tests. The latter researchers also state that the more bearish or bullish the markets are, the bigger the deviations of β are. Also, regarding α, deviations increase as uncertainty increases, for speculators demand higher compensation to enter a futures contract and hedgers require more contracts to protect their spot positions.

As explained in 1.1.4.6 the presence of a risk premium causes markets to be in backwardation or contango. According to Keynes (1930), backwardation or contango depends on whether speculators stand on the long position or short position respectively, matching hedgers and speculators clearly regarding their positions. However, Anderson and Danthine (1983) argue that backwardation or contango (i.e. risk premium/discount) and rejection of the unbiasedness hypothesis occur if there is imbalance of futures sales and purchases for hedging purposes. This translates to imbalance between short and long hedgers. Such imbalances may arise for two reasons: firstly, when futures market deducts a component from futures spot market (for example the demand which arises for a storage company to store a particular commodity) and secondly due to asymmetric risk faced by hedgers (long and short). Besides, Sensoy and Hacihasanoglou (2014) mention that if futures prices truly carry information about expected spot prices, informed investors have to participate in both positions (long-short) of futures contracts.

Working (1953) opposes Keynes's (1930) theory by stating that futures price is equal to the expected spot price and speculators require a compensation for their different opinion about the expected spot price. Chang (1985) and Lee (2013) expand on Working's theory and reconcile it with Keyne's theory by arguing that speculators profit from either risk premiums or their forecasting ability (forecasting theory). The former researcher concluded that futures returns to speculators are due to risk premiums, thus supporting Keynes theory, however speculators displayed above average forecasting ability as well. The latter researcher concluded that there is not consistent evidence of backwardation or contango in markets, hence -sophisticated and large- speculators mainly profit from their forecasting skills and the unbiasedness hypothesis is confirmed due to the very presence of those superior speculators even in few numbers. However, temporal periods of backwardation or contango may also exist for particular markets.

1.2.3.2 Current Futures Price and Current Spot Price

Under the non-arbitrage argument, the cost of carry model, also known as theory of storage or theory of convenience yield, reviewed in chapter 1.4.4, provides the fundamental relationship between current prices of spot and futures markets, algebraically that is:

$F_t=S_te^{c\Delta T}$

where F_t and S_t are the current futures and spot prices respectively, ΔT is the time period between current time point and futures maturity date and c is the cost of carry. In logarithmic form, cost of carry transforms to: $f_t=s_t+c\Delta T$, where f_t and s_t are the natural logarithms of futures and spot prices respectively. The cost of carry model connects the contemporaneous values of spot and futures prices and implies that the two markets are co-integrated. Co-integrated futures and spot prices share a stochastic drift and are interpreted as evidence of markets being pricing efficient, in other words as evidence of a long-run relationship between futures and spot prices within the non-arbitrage band (Chen and Zheng, 2008). Ankamah-Yeboah et al. (2017) also distinguish between pricing efficiency which can be investigated through the cost of carry model and informational efficiency which can be investigated through the risk premium theory mentioned in 1.2.3.1. Silvapulle and Moosa (1999) argue that presence of co-integration is a prerequisite for market efficiency, hence for unbiasedness hypothesis as well, and in the case that current spot and futures price are not linked, the cost of carry model can be used to reject the unbiasedness hypothesis. On the other hand, if prices are co-integrated no further conclusion can be made for the unbiasedness hypothesis. Thus, under the market efficiency framework, co-integration is a necessary condition but not a sufficient one.

If the cost of carry is supported, spot and futures prices should be linked with the co-integrating vector (1, -1). Theissen (2012) flags the issue of daily changes in potential co-integrating relationships using the cost of carry model due to term c∆T and suggests the examination of discounted futures prices and spot prices. Milunovich and Joyeux (2010) are also concerned about the stochastic nature of interest rates in the model. They suggest that c∆T be viewed as a third variable, apart from spot and futures prices, hence concluding to the examination of co-integrating vector (1, -1, -1). Gwilym et al. (2019) are also cautious with the frictionless markets assumption implied by the cost of carry model. They argue that heterogeneity of agents (short-hedging producers, long-hedging consumers and speculators) can create multiple time-varying equilibria and erratic pricing behaviours as traders move in and out of markets.

The cost of carry model does not restrict the existence of short-run dynamics. Regarding commodities, Jena et al. (2018) argue that demand shocks have an enduring influence on production and spot prices and can easily disrupt the long-run relationship of futures and spot prices. On the other hand, supply and storage-related shocks have temporal influence on markets. The cost of carry model evolves through the interactions of those shocks and while all shocks provoke trading, their consequences in financial markets depend on their nature. Thus economic reasoning justifies the co-existence of co-integration and short-run causal dynamics; a long-run relationship is brewed through demand innovations and short-run dynamics grow out of supply and storage innovations, and also taking into consideration the different reaction times of markets. Besides, Nicolau and Palomba (2015) state that co-integration implies at least unidirectional causal effects.

Additionally, considering that futures and spot markets ‘‘compete’’ for the price discovery process, relationships between contemporaneous futures and spot prices can be used as indicators for dominance of one of the two types of markets. In literature, dominance in price discovery process is examined either in terms of relative contribution or in terms of information flows and transmissions. Regarding relative contribution, information shares (Hasbrouck, 1995) and common factor weights (Gonzalo and Granger, 1995) are the most common techniques used, while regarding information flows and transmissions, the lead-lag relationships between futures and spot prices are examined via causality tests. The main reason that lead-lag relationships between futures and spot markets concern researchers and investors is the implicit examination of market efficiency -in terms of informational efficiency- and of price discovery process (Silvapulle & Moosa, 1999). However, Asche et al. (2016) and

Ankamah-Yeboah et al. (2017) suggest that prediction hypothesis be used for evidence of long-run price discovery dominance. They also argue that futures markets are suitable hedging tools only if they lead spot markets in long-run price discovery and if unbiasedness hypothesis holds.

1.2.3.3 Lead-Lag Relationships and Causality

Regarding the lead-lag relationships between futures and spot markets, and considering the fact that those markets refer to the same underlying assets and the theories of non-arbitrage and efficient markets, any causality tests between futures and spot markets should theoretically conclude that neither market dominates the other. However, this is not the case in practice. The possible scenarios in futures and spot markets dynamics are presented in the following sub-sections.

1.2.3.3.1 Futures markets lead spot markets (F→S)

From empirical studies this is the most common conclusion. Futures markets lead spot markets and come out as relatively more efficient. Most researchers attribute this type of relationship to the lower transaction costs of futures markets (trading cost hypothesis). Thus, futures markets react faster to information arrivals than spot markets do. Judge and Reancharoen (2014) suggest looser regulation and potential constraints of short selling in spot markets as possible factors of futures markets dominance. Additionally, as derivatives are leveraged financial instruments, investment financing is less in the case of futures (leverage hypothesis) (Fleming et al., 1996). Moreover, regarding assets with storage constraints, futures could prove a better solution than acquiring the underlying asset, especially for speculators who are not interested in the latter per se (Silvapulle & Moosa, 1999). Also, futures markets generally attract well-informed investors, especially speculators, who contribute more skillfully in price discovery than their counterparts do in spot markets. Moreover, regarding commodities, futures markets can be used as a tool by big players of spot markets in order to manipulate competitors regarding production decisions (Newberry, 1992; Bekiros and Diks, 2008). Finally, according to Moosa and Al-Loughani (1995) both arbitrageurs and speculators use futures prices as their reference point for their strategies.

1.2.3.3.2 Spot markets lead futures markets (S→F)

An explanation of this relationship was given by Silvapulle & Moosa (1999); transactions by investors who trade exclusively in spot markets provoke a change in spot price. Then, arbitrageurs detect deviations in the cost of carry model and reform futures price. Lastly, speculators notice expectation differentials and cause further changes in both prices. Asche et al. (2016) suggest that the leading role of spot markets implies that futures markets suffer from immaturity and lack of investor heterogeneity.

1.2.3.3.3 Bidirectional lead of both markets (feedback) (F↔S)

In this case futures prices may predict spot prices and vice versa. The markets exhibit rather erratic reactions to information arrival. Kawaller et al. (1987) argue that futures-spot relationship is dynamic over time and new information are processed depending on each investor's position. There are times when futures lead and times when spot prices lead. They also mention that both futures and spot prices are influenced by past futures and spot prices, thus suggesting for market inefficiency. Lin et al., (2018) state that time varying lead-lag relationships are partially due to time varying investor sentiment. The role of futures markets in price discovery process in the long-run and their leading role in the short-run decreases with high investor sentiment. When investor sentiment is driven up, noise trading also increases and this in turn increases trading risks and costs. Due to the unpredictability of noise traders, informed investors of futures markets withdraw from trading a bit, thus their information are not utilized and not integrated in prices. Also arbitrageurs cannot take as aggressive positions against potential arbitrages as they would want to. Hence futures markets may partially and temporarily concede dominance to spot markets. Furthermore, Moosa (1996) suggests that external shocks may disrupt an already unidirectional lead of futures markets and result in bidirectional lead. Other researchers, such as Shu and Zang (2012), interpret bidirectional causality as simultaneous absorption of information.

1.2.3.3.4 Neither futures nor spot markets lead (independence)

In case there is not a lead-lag relationship, the spot and futures prices are not co-integrated as well. No prediction can be made for futures and spot prices considering lagged spot and lagged futures prices respectively. Futures and spot markets are at the same levels of efficiency. Price discovery is a process that happens independently in the two markets.

Investigation of causality could help, at least theoretically, investors realize and employ appropriate investment strategies. Also, regulators can improve the functionality of the markets through their understanding of the traders' incentives and keep the balance between hedgers and speculators. While hedgers treat futures market as their secondary field for risk management purposes, speculators treat futures market as their priority and dedicate their resources in finding out regularities which they can exploit. Although speculators contribute positively to the markets by increasing liquidity, they pose a threat to the efficiency of futures markets if they can consistently predict prices (Hossefeld & Rothig, 2016).

Focus of literature review was given on recent studies, with the exception of some seminal works of previous decades. The main reason is that technological advancement and the recent crisis accompanied by the collapse of Lehman Brothers have changed the way financial markets function. Regulation has been stricter for exchange and OTC markets, and new venues, such as ATS, ECN, dark and grey pools have risen and claim significant share of overall trading. Furthermore, electronic trading and the evolution of algorithmic and high frequency trading have changed microstructure, liquidity and transaction costs and, in turn, price discovery process (Kissell, 2006). Although outdated implications cannot be totally avoided, recent studies would provide a better comparison for the results of this work. Only studies on commodities and indices were considered, for there is not enough research conducted on other assets. Some of the articles reviewed below also examine volatility spillovers. The corresponding results are also presented for review completeness only and not for comparison purposes, for causality-in-variance is out of the scope of this work.

1.2.4 Causality Studies on Commodities

Regarding commodity markets, most of research has been conducted on assets of the energy, metal and agricultural sectors. There are also some researchers who examined assets from various commodity sectors.

1.2.4.1 Energy

Trading of energy futures started in 1970s due to the high volatility of energy assets prices during that period. Nowadays, there are future contracts in a variety of energy commodities, including crude oil and its derivative products, natural gas, electricity, biofuel and emissions. The largest markets are the NYMEX (as part of the CME Group) and the ICE, attracting both financial professionals and physical market stakeholders (Simkins and Jia, 2015). As of 2018, the energy derivatives accounted for 31% of commodity derivatives trading volume worldwide or for 1.8 billion contracts annually, with a huge boost of trading volume in Asia-Pacific markets in recent years. Yet, about half of trading still takes place in the US. The asset that mostly lures traders is crude oil (WFE, 2019). According to Dergiades et al. (2018), observation and potential prediction of prices in the energy sector is a priority for many stakeholders due to the long horizon planning of energy projects.

The research in lead-lag relationship in energy futures and spot markets is extensive, especially for crude oil. However, the results are mixed and there is no consensus about which the leading market is, if there is any at all.

Silvapulle and Moosa (1999) studied crude oil market using daily data, from 2 January 1985 to 11 July 1996. Observations included spot prices for WTI crude oil and the corresponding one, three and six-month to maturity futures contracts traded on the NYMEX. Deploying VAR models and the Hsio (1981) approach based on Akaike's final prediction error (FPE) criterion for linear causal effects and the Back and Brock (1992) model on VAR-filtered residuals for non-linear effects, they ended up with mixed results; linear approach indicated that futures lead spot market, while non-linear approach showed bidirectional causality between futures and spot markets for all maturities. Re-applying the non-linear tests to EGARCH-filtered residuals, they discovered that part of non-linear dynamics was due to volatility transmissions.

In one of the most cited studies, Bekiros and Diks (2008) examined causal effects between futures and spot markets of crude oil. They used two periods of daily data, from 21 October 1991 to 29 October 1999 and from 1 November 1999 to 20 October 2007, in order to control for OPEC regulation changes regarding oil spare capacity. Data included WTI oil spot prices and the corresponding futures contracts of one to four months to maturity, traded on the NYMEX. Employing pairwise VEC models for linear Granger causality, they detected substantial bidirectional causality for both periods. Additionally, applying the Diks and Panchenko (2006) non-parametric test on the VECM-filtered residuals to ensure for non-linear causality, they also found bidirectional causality for the first period, but mainly unidirectional causality from futures to spot prices for the second period. Re-applying the Diks and Panchenko (2006) test on GARCH-BEKK-filtered residuals they also concluded that substantial part of non-linear dynamics was due to volatility spillover effect. Repeating the same procedures but this time for a multivariate 5x5 model, they spotted linear dominance of spot over futures prices for the second period. Besides, the non-parametric approach revealed a non-linear feedback mechanism for the first period, and futures dominance for the second period. Again, GARCH-BEKK-filtered residuals proved that much of the non-linear dynamics was due to volatility transmissions.

Huang et al. (2009) gathered daily observations, from 2 January 1986 to 30 April 2007, for WTI crude oil spot prices and its corresponding futures. Three sub-periods were defined considering two breaks due to the Gulf War and the 11 September attack. Two methodologies were used, firstly a conventional linear VEC model after confirmation of Engle-Granger co-integration, and secondly a three regime threshold VEC model considering the magnitude of the basis and the arbitrage band. The conventional VEC model indicated unidirectional causality from futures to spot prices for the whole sample and first and third sub-periods, and bidirectional causality for the second sub-period. The threshold VEC model provided mixed results as expected. Under the first regime (strong contango), there was found no causality for the whole sample and the first sub-period, unidirectional effects from futures to spot for the second sub-period and bidirectional effects for the third sub-period. Under the second regime (no-arbitrage zone), no causality was detected at all. Under the third regime (strong backwardation), spot prices lead futures for the whole period and bidirectional lead-lag relationship was spotted for the first and second sub-periods. No causality was uncovered for the third sup-period.

Alzahrani et al. (2014) investigated causality between futures and spot oil prices in both time and frequency domains, arguing that investors' heterogeneous horizons should be considered. Data included daily observations, from 20 February 2003 to 19 April 2011, for WTI spot prices and one, two, three and four-months to maturity futures contracts traded on the NYMEX. Applying a VEC model in the original series, they found linear bidirectional Granger causality between futures and spot prices. Wavelet transformation of data confirmed linear bidirectional causal effects for the short-term, using both a VAR and a VEC model for comparison reasons, while non-linear bidirectional causality was found for both short and long horizons, using a modified version of the Baek and Brock (1992) test on VECM-filtered residuals.

As part of their study, Chen et al. (2014) approached causality in crude oil market considering potential structural breaks. Monthly observations were used, from January 1986 to December 2012, for WTI spot prices and one-month to maturity futures of the NYMEX. Employing both a VEC model for linear causal effects and the Diks and Panchenko (2006) test for non-linear effects, the authors examined the full sample period and two sub-periods after considering a structural break in July 2004. Linear testing concluded that spot prices lead futures prices for the whole period and the second sub-period. Adversely, non-linear testing revealed that futures prices Granger-cause spot prices for the full sample and the first sub-period.

Balcilar et al. (2015) examined the lead-lag relationship of spot and futures prices in the crude oil market following two different methodologies; in the first one, Toda and Yamamoto (1995) causality test was used for the whole data period, while in the second one, a Markov-switching VEC model was utilized, thus enabling the researchers to stochastically divide the sample into regimes. Daily observations, from 2 January 1986 to 31 July 2013, included WTI spot prices and futures prices of one, two, three and four-month maturity contracts traded on the NYMEX.

The results for the whole sample confirmed bidirectional causality between spot and futures prices of crude oil. However, direction and strength of causality are not consistent under the regime switching approach; particularly it was found that there is no causality at all during serene market conditions, while there is bidirectional causality or unidirectional causal effects from futures to spot prices and vice versa in volatile market periods, particularly related with geopolitical events in Middle East and East Asia. Lastly, there was evidence of futures prices predictive power over spot prices on the long run.

Arfaoui (2018) investigated conventional and cross causality between futures and spot prices of crude oil and refined oil, the latter being proxied by gasoline and heating oil. Monthly data were obtained, from January 2007 to April 2015, and one-month to maturity futures traded on the NYMEX was used. After co-integration confirmation, a multivariate 6x6 VEC model was used for Granger causality examination. Interestingly, it was found that crude oil spot prices are Granger-caused by heating oil futures but not by crude oil futures prices. Also, while gasoline and heating oil spot prices Granger-cause crude oil future prices, crude oil spot prices do not. As for gasoline, there is evidence of bidirectional causality between its spot and futures prices. Furthermore, in view of heating oil, its futures prices lead the spot prices but they are Granger-caused by the crude oil and gasoline spot prices.

Shao et al. (2019) deployed the symmetric thermal optimal method (TOPS) to study the crude oil market. Data consisted of daily, weekly and monthly observations, from March 1987 to October 2017 with slight adjustments to the sample period with regard to the different frequencies used. The NYMEX traded futures contracts of one, two, three and four months to maturity were used, as well as WTI crude oil spot prices. Results indicated bidirectional causality for daily and weekly data for futures of all maturities. For monthly data, spot prices were found to lead futures for the period 1987-1999 and to follow them for the period 1999-2007. Bidirectional causality was observed for the period 2007 onwards. As a conclusion, it was argued that no consistently dominant market could be found and direction and strength of causality are volatile and subject to geopolitical events influencing oil markets.

Ghoddusi (2016) examined Granger causality in the natural gas market by considering different types of gas, namely wellhead, industrial, residential, commercial, power and citygate gas. Monthly data, from June 1990 to December 2014, contained six different gas spot prices with respect to its use, and gas futures contracts traded on the NYMEX with maturities of one, six and twelve months. Using the traditional Granger causality test through a VEC model, Ghoddusi ended up with mixed results. In the case of wellhead and industrial gas, there was no causality detected, in the case of power gas, bidirectional causality was spotted and in the case of commercial and residential gas, futures of all maturities led spot prices.

Zhang and Liu (2018) also inspected lead-lag relationship of futures and spot prices of natural gas. Using daily data, from 7 January 1997 to 27 February 2016, and the first four nearest to maturity futures contracts traded on the NYMEX, they divided the sample into two sub-periods and they used the conventional VECM approach and the

Diks and Panchenko (2006) method. The study ended up with mixed outcomes; linear Granger causality detected unidirectional lead lag relationship from futures to spot prices, while the Diks and Panchenko (2006) test on raw data and the VECM-filtered residuals resulted in bidirectional causality for both sub-periods. The non-linear test was also applied to GARCH-BEKK-filtered residuals to conclude that non-linear causal dynamics were partly due to volatility spillovers.

Dergiades et al. (2018) used daily data, from 7 January 1997 to 30 July 2013, including gas spot prices and the corresponding front month futures contract of the NYMEX. Deploying firstly the standard Granger causality test with VEC modelling and secondly a frequency domain analysis to capture non-linear dynamics, with and without controlling for weather conditions as an exogenous variable, they uncovered the leading role of futures over spot gas prices under both methodologies. The examination of the VECM filtered residuals under the frequency domain analysis showed that the futures dominance endured the de-meaning step for low and medium frequencies, while the examination of the GARCH-BEKK filtered residuals showed that almost all of the futures predictive power over the spot market was due to volatility transmissions.

Moving on to electricity, Ballester et al. (2016) examined the daily data, from 1 January 2007 to 31 December 2014, of SPEL index of MIBEL market in Spain and the corresponding futures and forwards contracts of one-month, one-quarter and one-year to maturity traded on OMIP and OTC markets respectively. Under VEC modelling, they found bidirectional causality between one-month futures and spot prices, while one-quarter futures Granger causes spot market. Furthermore, evidence that futures lead forwards was found as well, explained by the investors’ confidence in futures markets.

As part of their study about electricity futures pricing in Finland, Junttila et al. (2018) inspected causal effects between futures and spot market. Data included monthly observations, from January 2006 to January 2016. In particular, the underlying asset examined was the difference between Finnish electricity spot price and average Nordic area electricity spot price, obtained from Nord Pool and the respective closest to maturity EPAD futures contract traded on Nasdaq. Using a VAR model for conventional Granger causality, but not checking for potential long-run equilibrium between the series, there was evidence of the leading role of spot prices over the futures contract.

Milunovich and Joyeux (2010) studied the European carbon market of phase I (2005-2007) of Kyoto Protocol. Daily observations, from 24 June 2005 to 27 November 2006, consisted of EUA carbon spot prices obtained from Powernext, three futures contracts with maturity in December 2006, 2007 and 2008 obtained from European Climate Exchange (ECX), and Euribor interest rate values. Co-integration was found between spot prices, interest rates and December 2006 and 2007 maturity futures contracts. Using the Toda and Yamamoto (1995) approach for co-integrated series and a conventional VAR model for non-co-integrated ones, the authors found that there is bidirectional causality between spot prices and futures of maturity in December 2006 and 2007. On the other hand, there was evidence of the leading role of futures of December 2008, justified by the fact that futures contracts of 2008 referred to spot prices of phase II (2008-2012) which came into effect well after the sample period of this study. Additionally, volatility spillovers were examined under a BEKK-GARCH approach resulting in the discovery of bidirectional causality in-variance between spot prices and futures of 2007.

Arouri et al. (2012) examined causality in European carbon emission markets of phase II of EU ETS. Daily observations, from February 2008 to March 2010, included EUA carbon spot price and particularly the December 2010 maturity futures contract traded on Bluenext. Deploying a VAR model for linear causality, they detected bidirectional causal effects in-mean and in-variance. They also practiced a Switching Transition Regression EGARCH model to capture non-linear causality in bearish and bullish regimes. The non-linear approach also detected bidirectional causal effects.

Rittler (2012) examined the carbon market in first and second conditional moments and in high frequency. Data, from 1 May 2008 to 15 December 2009, included daily, 30-minute and 10-minute observations of spot prices obtained from Bluenext and December 2008 and 2009 maturity futures contracts obtained from ECX. Apart from the full sample period examination in which the most active of the two-2008 and 2009 expiration date- future contracts was used, two sub-periods, from May 2008 to December 2008 and from January 2009 to December 2009 were also examined, in which the December 2008 and the December 2009 futures contracts were used respectively and exclusively. Using the Engle-Granger approach, the author found co-integration evidence for the 30-minute and 10-minute data only, for all samples. Applying a VEC model, it was found that futures leads spot market for daily data and for the whole sample period, but there is bidirectional causality in the higher frequency data. For the sub-periods and the 30 and 10-minute intervals data, bidirectional causal effects were also spotted. Causality in-variance was checked only for the 10-minute observations deploying an unrestricted extended CCC-GARCH model suggested by Conrad and Karanasos (2010). For all periods, unidirectional futures to spot market volatility spillovers were detected.

Philip and Shi (2015) also studied causal effects in-mean and in-variance for carbon markets. The 15-minute interval data, from 30 April 2009 to 31 December 2011, included carbon spot prices from Bluenext and the most active futures contract from Intercontinental Exchange (ICE). The sample was split in quarters. Causality in-mean was tested with a VAR model which indicated bidirectional lead-lag relationship for all quarters, with the spot to futures causal effect power enhanced just before the allowance submission deadlines. Causality in-variance was tested with the HAR-RV model by Corsi (2009); the results are mixed for the short, medium and long-term coefficients and for different quarters, but it is noteworthy that the spot market creates unidirectional volatility spillovers to futures for the period before the deadlines and the direction of spillovers is reversed after the deadlines.

1.2.4.2 Metals

Non-precious metals derivatives account for 26% of commodity derivatives global trading volume or 1.5 billion contracts annually. On the other hand, market share of precious metals derivatives is less than 5% (WFE, 2019). Shanghai Futures Exchange, Dalian Commodity Exchange and London Metal Exchange are the main markets for non-precious metals, while CME Group and Shanghai Futures Exchange are the dominant markets for precious metals. Steel Rebar future contract of 10 tons/lot traded on Shanghai Futures Exchange was the most traded commodity derivative in the world in 2018.

As part of their study, Chen and Lin (2004) studied causal effects between spot and futures in lead market. Quarterly data, from December 1964 to June 1995, contained spot prices of the London Metal Exchange (LME) and three-months to maturity futures. Two methodologies were used, firstly the conventional Granger causality and secondly, the Baek and Brock (1992) method for non-linear causality. Both VAR and VEC models were used for linear causality, though data showed evidence of co-integration. Linear approach found no causality in VAR models, but it uncovered bidirectional causality in VEC models. On the other hand, non-linear approach detected a lead-lag relationship from spot to futures when applied to VAR filtered residuals, but it lost this detection when applied to VECM filtered residuals.

Arouri et al. (2013) partially and indirectly examined potential causal effects in aluminum market. Using weekly data, from January 1979 to December 2010, and including the LME aluminum spot prices and the corresponding three-months to maturity futures contract, also traded on the LME, they applied an EC model, an augmented EC model with GARCH in-mean effects and a non-linear Exponential Switching Transition EC model. The results were consistent for all methods that futures can predict spot prices, but the reverse relationship was not examined, thus no leading roles can be determined.

Fernandez (2016) examined the case of non-ferrous metals traded on the LME, namely aluminum, copper, lead, nickel, tin and zinc, using daily spot prices from January 1991 to May 2015 and considering the corresponding three and 15-months to maturity futures contracts. Deploying VEC models and after controlling for inventory levels, she found that short maturity futures dominate spot prices, with the exception of bidirectional causality for aluminum, whereas she spotted no causality between long maturity futures and spot prices, with the exception of unidirectional spot to futures causality for tin and copper.

1.2.4.3 Agriculture

Agricultural derivatives account for 32% of all commodity derivatives trading volume worldwide, or for 1.9 billion contracts annually. Asia-Pacific region dominates trading with market share of about 50% (WFE, 2019).

He and Xie (2012) studied Chinese sugar market, using daily data, from 6 January 2006 to 21 September 2009. Observations included sugar wholesale spot prices and futures traded on the Zhengzhou Commodity Exchange (CZCE). After confirming for co-integration, they applied a VEC model for Granger causality which spotted a unidirectional lead-lag relationship from futures to spot prices.

Studying the case of live cattle, Amarante et al. (2018) used daily data from 10 January 2000 to 30 December 2014 for the spot prices of beef cattle and the corresponding futures contracts traded on the BM&FBOVESPA in Brazil. The classical Granger causality procedure through a VEC model resulted in bidirectional causality between futures and spot prices.

Yan and Guiyu (2019) investigated the cornstarch market in China, using daily observations, from 19 December 2014 to 23 November 2017. Spot prices from the CSIA and the highest open interest futures traded on the DCE were used. Practicing Granger causality test in a VAR model despite the evidence of co-integration, the authors found that futures dominate spot prices.

Agyekum et al. (2017) used daily data, from 4 January 2013 to 2 March 2016 to examine causal effects in Chinese cornstarch market. Spot price observations came from the average cornstarch price of twenty major domestic cities and futures came from the Dalian Commodity Exchange (DCE). Using a VEC model for conventional Granger causality, after confirming for co-integration, it was concluded that futures lead spot prices.

Regarding salmon markets, Asche et al. (2016) explored the unbiasedness hypothesis and price discovery process for risk management purposes. Monthly data, from June 2006 to June 2014, combined spot prices of Fish Pool Index (FPI) and futures of one to six months to maturity, traded on the Fish Pool Exchange of Norway. Johansen (1988, 1991) co-integration tests confirmed the unbiasedness hypothesis and showed that spot prices lead futures of all maturities in the long-run and price discovery happens in the spot market.

Ankamah-Yeboah et al. (2017) also investigated salmon markets using monthly data from June 2006 to June 2015. Salmon spot price was proxied by Fish Pool Index offered by Fish Pool ASA Exchange of Norway. One to twelve-months to maturity futures traded on the same market were also used. Conventional Granger causality was investigated with either VAR or VEC models with respect to co-integration results. It was found that spot prices lead futures of one, two and six-months to maturity, while futures of three, four, five, nine and twelve-months to maturity lead spot prices.

1.2.4.4 Mixed Commodity Studies

Yang and Zhang (2014) studied Chinese metal and agricultural markets, specifically aluminum, copper, zinc, bean, sugar and cotton markets. They used daily observations, from 9 May 2008 to 20 November 2012, for spot prices and one-month to maturity futures contracts obtained from the Shanghai Futures Exchange (SHFE) and the Zhengzhou Commodity Exchange (CZCE) for metal and agricultural futures respectively. Using two different methodologies, a VAR model for conventional Granger causality and a frequency domain method suggested by Breitung and Candelon (2006), they ended up with consistent results. According to both methods, there is bidirectional causality for all commodities, except for the dominance of aluminum futures over spot prices. Additionally, despite the bidirectional lead-lag relationship, the frequency domain approach clearly indicated that futures causal effects are stronger than those of spot markets in almost all frequencies, except for bean market in which futures and spot prices impacts are of equal power. One potential objection to the study is the neglect of an ECT in VAR modelling, despite the confirmation of Johansen co-integration.

Similarly, Joseph et al. (2014) examined the two most traded commodities in each of the energy, agricultural, precious and non-precious metal sectors of India, namely crude oil, natural gas, chana, soybean, gold, silver, aluminum and copper. Using daily data, from 3 January 2008 to 31 December 2012 of the Multi Commodities Exchange and National Commodity and Derivatives Exchange for spot prices and the nearest to maturity futures, they examined Granger causality deploying VAR models and a frequency domain analysis. The former method showed that futures dominate spot prices for all commodities except for silver, crude oil and natural gas for which a feedback causal relationship was found, while the latter method showed complete dominance of futures prices for both high and low frequencies and for all commodities.

Nicolau and Palomba (2015) examined causality and endogeneity between gold, oil and gas futures and spot prices deploying the Toda and Yamamoto (1995) method and recursive analysis. Daily observations were used from 7 January 1997 to 30 May 2014. Gold, oil and gas spot prices come from London PM Fix, WTI and Henry Hub closing prices respectively, and futures contracts come from the NYMEX for oil and gas and from the COMEX for gold. For gold and oil, bidirectional causality was found, while for gas, futures lead spot prices. The results were also found to withstand after controlling for the crisis of 2008.

Jebabli and Roubaud (2018) examined efficiency in agricultural and energy markets. Using daily data, from 1 December 2000 to 17 August 2015, for corn, soybean and crude oil spot prices and the respective one-month to maturity futures contracts traded on CME, they deployed a conventional VEC model after testing for Johansen co-integration and a threshold VEC model after testing for threshold co-integration with supLM statistic of Hansen and Seo (2002). The former approach showed bidirectional causality for corn and soybean markets and unidirectional causal effects from spot to futures for crude oil. The latter approach determined three regimes with respect to basis divergence. Under the low divergence regime, corn and soybean futures lead their respective spot markets, while there is bidirectional lead-lag relationship in the case of crude oil. Under the middle divergence regime, there is bidirectional causality in the case of corn markets. Lastly, under the high divergence regime, bidirectional causality was uncovered for all commodities.

Jena et al. (2019) investigated causality in gold, silver, crude oil and natural gas using the causality in-quantiles method suggested by Balcilar et al. (2016) and dividing markets into bearish, bullish and normal states. This method also allowed the researchers to examine causality in variance, as well as in mean. Data included daily spot prices of the four commodities in question and the corresponding nearest to maturity futures contracts traded on Multi Commodities Exchange of India. Regarding gold and silver, futures lead spot prices in mean for all market conditions, but there is bidirectional causality in variance for tranquil and bullish conditions. Natural gas futures lead spot prices both in mean and in variance, whereas for crude oil, there is unidirectional causality from futures to spot prices in mean and bidirectional causality in variance. Generally however, causal dynamics decrease for all commodities as markets move to extreme bullish or bearish conditions.

As part of their study, Cagli et al. (2019) examined WTI crude oil, Brent oil, heating oil and natural gas from the energy sector, gold, silver, platinum, palladium from the precious metals sector and aluminum, copper, zinc, nickel, lead and tin from the base metals sector. Using daily data, from January 1985 to February 2019, and deploying the Diks and Panchenko (2006) method on raw data and VAR filtered residuals, they discovered strong bi-directional causal dynamics for all energy assets and all precious metals. Regarding base metals, feedback dynamics were found for copper, lead and tin and unidirectional causality from spot to futures for aluminum, zinc and nickel.

1.2.5 Causality Studies on Financial Indices

Most studies in causality between futures and spot indices refer to stock indices. Trading of futures indices started in 1982 with the introduction of S&P 500 Index futures (Silber, 1985). Nowadays, top exchanges in this field are B3 SA Brasil Bolsa Balcao (formerly, BM&FBOVESPA), CME Group and Eurex, and the underlying indices of top futures are Bovespa Mini Index, E-mini S&P500 and EURO STOXX50. As of 2018, annually aggregate trading volume of futures indices was about 3.3 billion contracts, yet second to options indices volume (WFE, 2019). One peculiarity of stock indices is that the stocks, which the index consists of, may be of low interest to investors and infrequently traded. Hence, potentially outdated stock spot prices may lead to spurious dominance of futures in the lead-lag relationship investigation (Theissen, 2012).

As part of their study, Kasman and Kasman (2008) examined the long and short-term causality between Istanbul Stock Price Index 30 (ISE-30), traded on the ISE (nowadays BIST) and its corresponding futures contract traded on TurkDEX. Data included daily observations, from 1 July 2002 to 8 October 2007, and Granger causality was tested by VEC modelling after checking for co-integration. Evidence was found that there is a lead-lag relationship from spot to futures market, both in long and short-term.

Li (2008) examined the US, UK, German, Brazilian, and Hungarian futures and spot markets through S&P 500, FTSE 100, DAX 30, BOVESPA Index and BSI respectively, using daily data, from 3 April 1995 to 12 December 2005. Two methodologies were followed, firstly the conventional VECM approach and secondly the Markov-switching VECM approach, controlling for high and low volatility regimes. Under VECM, it was found that futures lead spot market in the case of S&P 500, both in long and short-term. In the case of FTSE 100, spot lead futures market in the long-term, but this relationship is reversed in the short-term. Regarding DAX 30, BOVESPA and BSI, bidirectional causality was detected for both long and short-term. Under MS-VECM, the author argues that futures lead spot markets in tranquil periods, while spot markets dominate futures markets in turbulent periods. The results of MS-VECM were consistent for all indices.

Bohl et al. (2011) investigated Polish WIG20 Index and its corresponding futures traded on Warsaw Stock Exchange, using daily data, from 16 January 1998 to 30 June 2009. They also divided the sample into two sub-periods to control for change in regulations in Polish markets in December 2004 and the allowance of mutual funds in derivative trading. Running VECM-DCC-GARCH models, they spotted bidirectional causality in the long-term and the leading role of futures in the short-term. The results were consistent for the two sub-periods, although the magnitude of information flow in the long term from spot to futures market decreased in the second sub-period, a decline attributed to the entrance of sophisticated institutional investors to futures trading.

Pati and Rajib (2011) examined S&P CNX Nifty Index of the NSE of India and the corresponding closest to maturity futures. Using 5-minute observations, from 1 March 2007 to 31 January 2008, and deploying a VEC model for Granger causality, they detected unidirectional causality from futures to spot market. Additionally, they found bidirectional volatility spillovers using the BEKK-GARCH approach.

Judge and Reancharoen (2014) studied the potential causality between SET 50 Index of the Stock Exchange of Thailand and its corresponding nearest to maturity futures contract traded on the TFEX. Using daily data, from 28 April 2006 to 30 September 2011, and utilizing a VEC model for Granger causality, they found that spot market dominates futures market, possibly due to greater trading volume of the former.

Chinese markets in particular have attracted recent academic interest. Xie and Juang (2013) probed into Chinese CSI 300 of Shanghai and Shenzhen stock exchanges and its future contract with the highest activity, using daily data from 16 April 2010 to 13 April 2012. Through a VEC model, they uncovered spot dominance over futures in the long-run, but no lead-lag relationship in the short-term. The latter result was justified by the low frequency data used, as most lead-lag relationships between spot and futures markets are detected with utilization of intraday data. Additionally, testing for impulse responses, they found that futures market shocks have negligible effect on the spot market, while spot market shocks causes significant aftershocks to the futures market.

Yao and Lin (2017) analysed information flows between stock index futures and stock markets in China, using conditional and non-conditional Granger causality tests in VAR for direct and indirect causal effects respectively. In particular, daily data consisted of spot prices for 844 stocks of the Shanghai Stock Exchange and 902 stocks of the Shenzen Stock Exchange, and of futures prices for Shanghai and Shenzen 300 Index, China Securities Index 500 and Shangai Stock 50 Index. Non-conditional Granger causality test concluded that futures indices slightly lead stocks, while the result was reversed when conditional Granger causality test was applied.

Wang et al. (2017) also studied futures and spot prices of CSI 300. Data contained daily observations, from 16 April 2010 to 31 December 2014, along with one-minute intervals of those observations. Futures contract used was that with the highest trading volume. Applying a thermal optimal path (TOP) method to capture non-linear causality, the authors found inconsistent results regarding daily data, but they detected a five-minute dominance of futures over spot prices regarding high frequency data of one-minute intervals. Additionally, they confirmed the latter leading role of futures in sub-samples of bearish, bullish and turbulent market periods.

As part of their study to investigate implications of regulation change in Chinese markets in 2015, Hao et al. (2019), examined Granger causality between SSE 50, CSI 500 and CSI 300 and their respective futures. Using 5-minute intervals of daily observations from 16 April 2015 to 30 June 2017, and deploying a VEC model they found bidirectional lead-lag relationship for all indices and their futures. Results were consistent even after splitting the sample in sub-periods, before and after the stricter regulations implemented in Chinese financial markets in 2015.

Gong et al. (2016) examined CSI300, HSI and S&P500 Index and their corresponding futures with the largest trading volume. Daily observations were used, from 16 April 2010 to 14 January 2014. They practiced two methods, firstly Granger causality analysis with VEC models and secondly a thermal optimal path (TOP) analysis. The results for both methodologies showed that spot leads futures market in the case of CSI300, while futures market leads spot market in the case of HSI and S&P500 Index. A possible explanation for the outcome is that CSI300 is traded on the developing market of China, while HSI and S&P500 Index are traded on the developed markets of Hong Kong and US respectively.

Moving on to non-stock indices, Shu and Zhang (2012), examining VIX and its futures traded on the CBOE, found mixed results. Daily data, from 26 March 2004 to 20 May

2009, included VIX spot value and the four nearest to maturity futures. Using VEC models, they found that the two nearest to maturity futures lead spot value, while there is no causality between spot value and the rest of the futures contracts. However, splitting the sample period into twenty quarters resulted in no causality in general, except for a few quarters. Additionally, using an updated version of Baek and Brock (1992) causality test to VECM filtered residuals to capture non-linear dynamics, bidirectional causality was detected. Yet, the authors were cautious about the result, for distant lags seemed to have had the same predictive power as near lags did. In any case, any leading role of futures was accorded to institutional investors.

Lee and Mo (2016) also gathered daily observations, from 26 March 2004 to 30 September 2011, in order to investigate VIX and its closest to maturity futures contract. Applying a VEC model, they found no linear lead-lag relationship between the markets. However, an exponential smooth transition VEC-GARCH model detected non-linear bidirectional causality between futures and spot markets.

Generally, the results are mixed, although aggregate outcome tilts the balance in favor of futures domination which confirms the informal academic consensus that futures tend to lead spot prices. On the other hand, even results of different methodologies within the same study may vary, thus any conclusion should be approached cautiously.

1.2.6 Potential Issues in Previous Studies

Although extensive academic research has been conducted so far in lead-lag relationships between futures and spot markets, there are some issues which should be noticed.

Firstly, there is dissimilarity among studies in the data frequency used. Researchers use observations that range from one-minute to monthly intervals, usually without any further explanation for the choice of the particular data they use. Several studies that combined data of different frequencies demonstrated inconsistent results. Thus, it is reasonable to assume that lead-lag relationships have gone undetected due to inappropriate data frequency. Additionally, very few studies consider the split of their sample period into sub-periods or deal with the presence of different regimes or structural breaks, even if this is clear just by the graphs of raw data. Some typical examples include changes in regulations or governmental and institutional interceptions in financial markets, such as those after the collapse of Lehman Brothers, OPEC intervention in oil markets in 1999 and the heavily criticized T+1 regulation in Chinese spot markets in 2015.

Secondly, there are many different methodologies applied. The development of new econometric models justifies such a phenomenon. But this heterogeneity in analysis makes comparison among studies difficult. If different analyses are of equal power and capability, then they should be practiced simultaneously for robustness purposes. If new analyses are more powerful than old ones, then old researches are outdated with respect to analysis, as well as to data. Yet, they are mentioned in even the most recent studies for comparison reasons.

Moreover, very few studies justify their results. While they provide some general, opaque directions based on some broad assumptions in view of the differences between futures and spot markets, such as transaction costs and liquidity, there is no clear evidence or further investigation that the outcomes of the studies can be justified for the particular markets they refer to. To their defense, such explanations could be regarded as being out of the researchers' objectives.

Lastly, almost all studies present no trading strategy or regulatory advice, if any potentially exists considering the results and also considering in-practice obstacles. Extracting real markets data, analyzing them under a theoretical framework and returning them back without reconciling the two domains may offer no real economic value to investors. Two notable examples are brought up here to illustrate the point: Judge and Reancharoen (2014) found evidence of causality in Thai markets and they were able to form and present a strategy that outperformed the conventional buy and hold portfolio in real market conditions, at least for the out of sample data. Likewise, Brooks et al. (2001) found evidence of causality in the UK markets, but they also acknowledged that the strategies they came up with could not beat the passive portfolio, concluding that investors could not practically exploit the discovered causal effects and benefit from their study. Yet, not only is it mentioned in most studies that exploration of potential lead lag relationships can help investors and policy makers, but it is explicitly addressed as a primary objective for several studies to help those market stakeholders.

CHAPTER 2

As presented in Chapter 1, theory regarding causal dynamics between spot and futures markets consists of contradictory yet reasonable arguments supporting the leading role of either one of the two types of markets invariably or both of them in a time-varying framework. Literature review also showed inconsistent results regarding the direction of causality. While most of research conducted supports that futures lead spot prices, there is a substantial number of articles that provide support either for unidirectional causal channels from spot prices to futures or for a feedback mechanism. Hence, the puzzle associated with information flows and price transmissions between interrelated markets remains unsolved; are spot and futures markets efficient and do both of them incorporate news instantaneously into prices as the EMH theory suggests? Which market, if any, drives the price discovery process in the long and short-term? This chapter is concerned with the lead-lag relationships and Granger causal effects between spot and futures markets from the empirical perspective.

2.1 DATA

Totally, eight assets were investigated for the purposes of this work, in particular, WTI oil and natural gas from the energy domain, gold and silver from the precious metals domain, and four stock indices, namely DAX30 and CAC40 from European exchanges and SP500 and Nasdaq100 from the US exchanges. The data consist of daily observations, from 4 January 2010 to 4 November 2019.

West Texas Intermediate (WTI) crude oil. The data for oil spot prices (dollars per barrel) derived from the US Energy Information Administration (EIA). The respective futures prices came from the Intercontinental Exchange (ICE). The futures contracts are traded in New York, London and Singapore and the futures list includes contracts with maturities of up to 108 consecutive months. The contract size is 1000 barrels with a tick of 0.01 dollars per barrel. Futures data used refer to contracts of one, two, three and six months to maturity (ICE code names T1, T2, T3 and T6 respectively). Total observations for WTI oil are 2542.

Natural gas. The data for (Henry Hub) natural gas spot prices (dollars per million Btu-or MMBtu) came from the US EIA, while the respective futures prices came from the NYMEX (CME Group). Futures contracts are deliverable and offered for maturities of every month for current calendar year plus twelve years more. The contract size is 10000 MMBtu with a tick of 0.001 dollars per MMBtu. The futures data used refer to contracts of one, two, three and six months to maturity (NYMEX code names NG1, NG2, NG3 and NG6 respectively). Total observations for natural gas are 2502.

Gold. The data for gold spot prices (dollars per fine troy ounce) stemmed from the London Bullion Market (LBMA), though benchmark is done by the ICE Benchmark Administration (IBA) twice per day at 11.00 (am spot price) and 15.00 (pm spot price) London time, with the former price being used in this work. The futures prices came from the COMEX (CME Group). The contracts are deliverable, refer to gold of 995 minimum fineness and are offered for maturities of up to three months plus for maturities of the February-April-August-October cycle for the next two years and of the June-December cycle for the next five years. The contract size is 100 troy ounces with a tick of 0.1 dollars per troy ounce. The futures data used correspond to the first, second, third and sixth contracts listed for delivery in chronological order (COMEX code names GC1, GC2, GC3 and GC6 respectively). Total observations for gold are 2523.

Silver. The data for silver spot prices (dollars per ounce) came from the LBMA, with benchmark done by the IBA once per day at noon, London time. The futures prices came from the COMEX. The futures contracts are deliverable, refer to silver of 999 minimum fineness and are offered for maturities of up to three months plus maturities of the January-March-May-September cycle for the next two years and of the July-December cycle for the next five years. The contract size is 5000 troy ounces with a tick of 0.005 dollars per troy ounce. The futures contracts used are the first, third and sixth listed to be delivered (COMEX code names SI1, SI3 and SI6 respectively). Total observations for silver are 2521.

DAX30. The German DAX30 index (Deutscher Aktien IndeX), given birth in 1988, consists of the stocks of the 30 leading companies quoted on the Frankfurt Stock Exchange. Depending on whether dividends are accounted for, it is distinguished in the performance DAX (total returns) and price DAX (no dividends), with the former being used in this work. The futures prices came from the Eurex. The future contracts have a multiplier of 25€, a tick of 0.5 points and are offered for maturities of the March-June-

September-December cycle. The first and second listed to be delivered contracts were used (Eurex code names FDAX1 and FDAX2 respectively). Total observations for DAX30 are 2499.

CAC40. The French CAC40 index, introduced in 1987 and named after Cotation Assistée en Continu system of the Paris Bourse (now Euronext Paris), consists of the stocks of the 40 leading firms quoted on the Euronext Paris. Contracts traded on the ICE Futures Europe (formerly, London International Financial Futures and Options Exchange-LIFFE) were used for futures pricing. The contracts have a multiplier of 10€, a tick of 0.5 points and are offered for maturities of every of the next twelve months. Futures of maturity of one and two months were considered (ICE code names FCE1 and FCE2 respectively). Total observations for CAC40 are 2523.

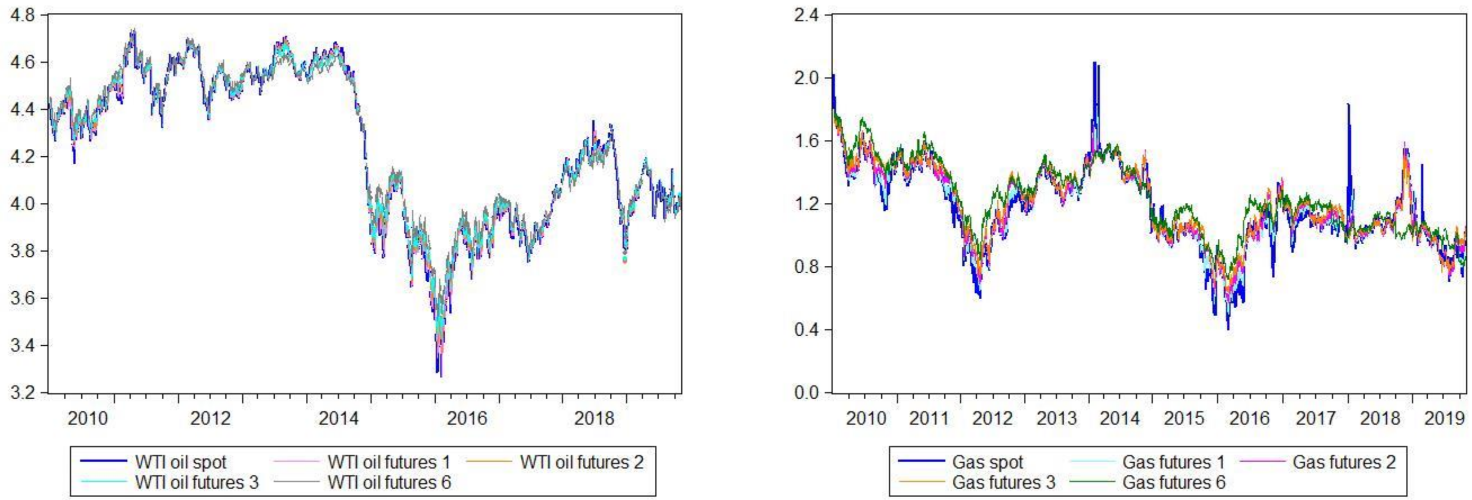
SP500. The US Standard and Poor's 500 index, created in 1957, consists of the 500 largest by capitalization firms in the US exchanges. The futures prices came from the E-mini SP500 contracts traded on the CME Group platforms. The contracts have a multiplier of 50$, one fifth of the standard contract, a tick of 0.25 points and are offered for maturities of the March-June-September-December cycle for the next five quarters (5 contracts available at any time). The first, second and third to be delivered contracts were used (CME code names ES1, ES2 and ES3 respectively). Total observations for SP500 are 2481.

Nasdaq100. The US Nasdaq100 index, created in 1985, is composed of the 100 largest non-financial firms traded on the Nasdaq Stock Market. The futures prices came from the E-mini Nasdaq contracts of the CME Group. The contracts have a multiplier of 20$, a tick of 0.25 points and are offered for maturities of the March-June-September-December cycle for the next five quarters (5 contracts available at any time). The first two contracts were considered (CME code names NQ1 and NQ2 respectively). Total observations for Nasdaq100 are 2502.

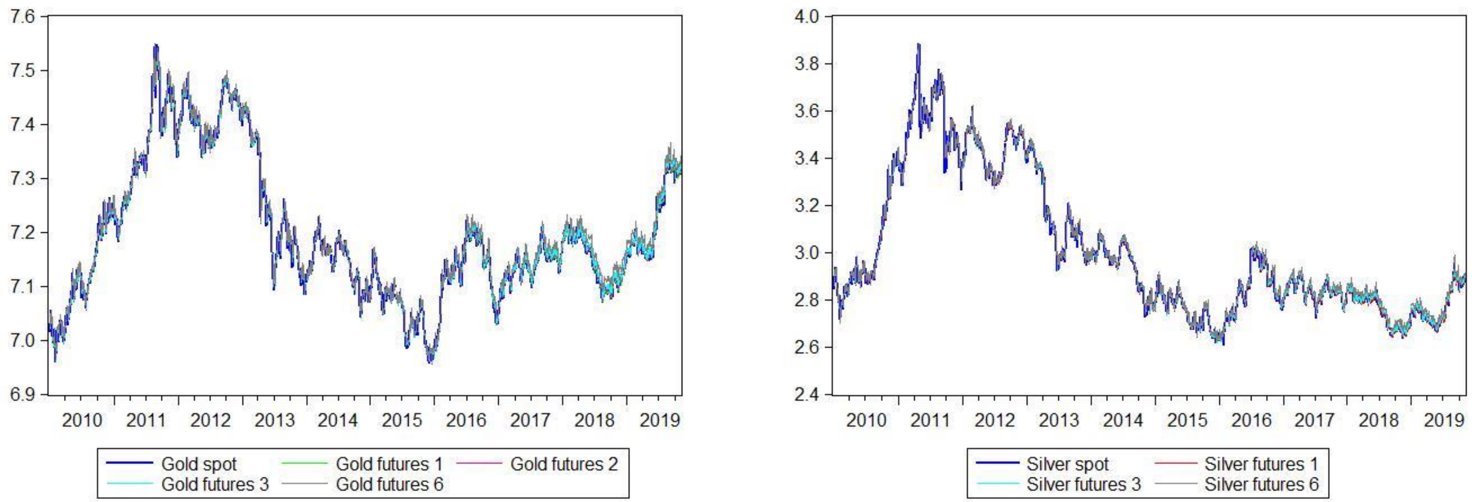
For the rest of this work, the adjusted symbols for the spot and futures prices are as follows: S for the spot price and F_X or FutX for the price of the futures contract which is the X^{th} one chronologically to expire among available contracts, but not necessarily expiring in X months (see available contracts and cycles above).

All asset spot and futures prices were transformed into logarithmic time series for further analysis. Graphs of the price time series (log levels) are presented in figures

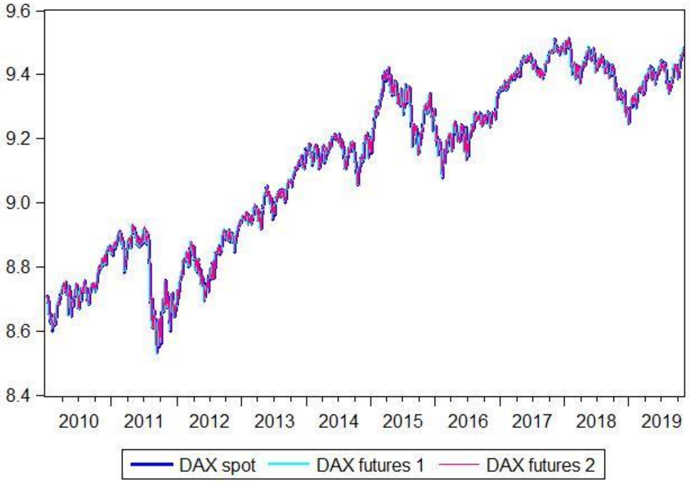
18(a to h), while the descriptive statistics for the returns (log first-differences) are presented in tables 2(a to h). Regarding returns, skewness is negative for gold, silver, DAX30, SP500 and Nasdaq100, hence standard deviation underestimates risk for these assets. Kurtosis is also substantial for all assets implying fat tails in the distributions. The standard deviation, compliant with Samuelson effect, decreases as the maturity of the futures contracts increases for all assets except for gold, SP500 and Nasdaq100. It is noted that the Jarque-Bera normality test p-value is p=0.0000 for all returns (not shown in tables), implying that returns do not conform to the normal distribution assumption. Also, the correlation matrices reveal substantially low correlation coefficients between spot prices and their corresponding futures prices for gold, silver and gas.

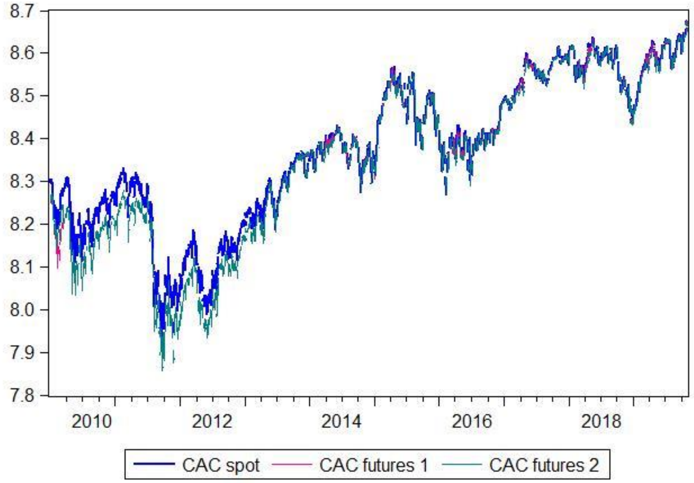


Figures 18(a) and 18(b). Graphs of spot and futures prices (log levels) for WTI oil and natural gas.

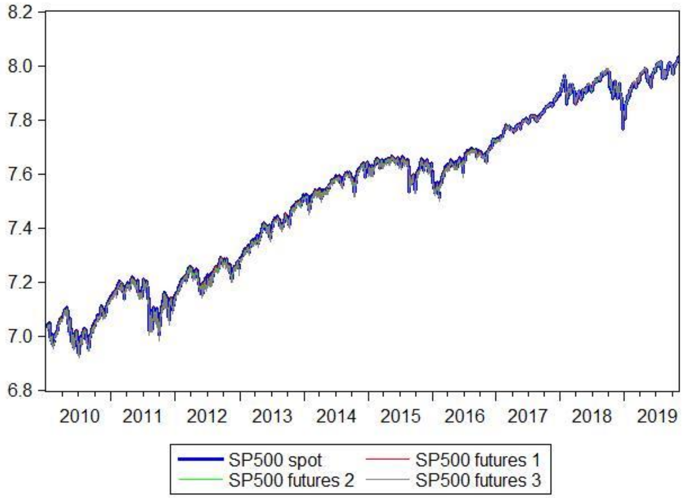


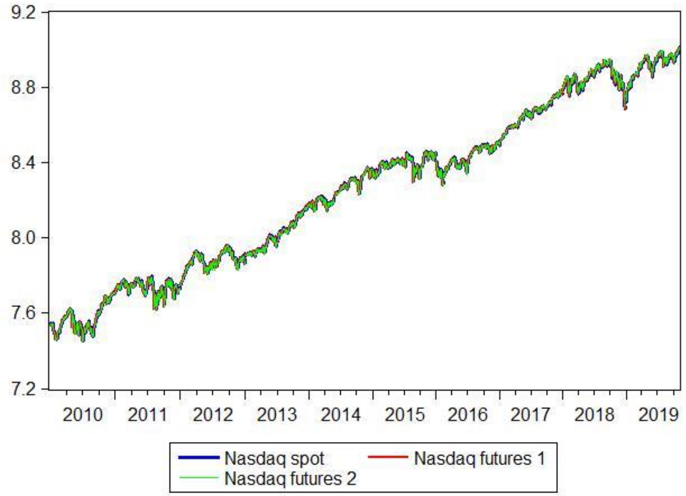
Figures 18(c) and 18(d). Graphs of spot and futures prices (log levels) for gold and silver.





Figures 18(e) and 18(f). Graphs of spot and futures prices (log levels) for DAX30 and CAC40.





Figures 18(g) and 18(h). Graphs of spot and futures prices (log levels) for SP500 and Nasdaq100.

Table 2(a). Descriptive statistics of spot and futures returns for WTI oil.

	Oil Spot	Oil Fut1	Oil Fut2	Oil Fut3	Oil Fut6
Mean	-0.000145	-0.000144	-0.000146	-0.000150	-0.000164
Std. Dev.	0.020787	0.020393	0.019820	0.019222	0.017888
Skewness	0.153071	0.136656	0.075898	0.031165	-0.077328
Kurtosis	6.782846	6.182011	6.017264	6.029405	6.018671
Jarque-Bera	1524.986	1079.913	966.3133	972.0574	967.3052
Correlation Matrix					
Oil Spot	1				
Oil Fut1	0.927838	1			
Oil Fut2	0.924384	0.982525	1		
Oil Fut3	0.922686	0.978581	0.995413	1	
Oil Fut6	0.910458	0.961588	0.983230	0.993232	1

Table 2(b). Descriptive statistics of spot and futures returns for natural gas.

	Gas Spot	Gas Fut1	Gas Fut2	Gas Fut3	Gas Fut6
Mean	-0.000315	-0.000294	-0.000280	-0.000284	-0.000366
Std. Dev.	0.040810	0.027986	0.025672	0.023595	0.018019
Skewness	0.598323	0.134638	-0.172995	-0.015219	0.032919
Kurtosis	37.15589	7.041462	8.548544	9.000499	6.760859
Jarque-Bera	121721.2	1709.634	3220.668	3752.221	1474.381
Correlation Matrix					
Gas Spot	1				
Gas Fut1	0.210340	1			
Gas Fut2	0.190920	0.942040	1		
Gas Fut3	0.179454	0.860670	0.952134	1	
Gas Fut6	0.183050	0.778742	0.799861	0.801972	1

Table 2(c). Descriptive statistics of spot and futures returns for gold.

	Gold Spot	Gold Fut1	Gold Fut2	Gold Fut3	Gold Fut6
Mean	0.000121	0.000119	0.000121	0.000122	0.000124
Std. Dev.	0.009612	0.009926	0.009927	0.009929	0.009914
Skewness	-0.588633	-0.741101	-0.743878	-0.748140	-0.759930
Kurtosis	10.12366	10.22205	10.22066	10.24833	10.34788
Jarque-Bera	5478.254	5711.804	5711.416	5756.169	5916.324
Correlation Matrix					
Gold Spot	1				
Gold Fut1	0.410523	1			
Gold Fut2	0.410537	0.999525	1		
Gold Fut3	0.410878	0.998932	0.999569	1	
Gold Fut6	0.411019	0.999217	0.999575	0.999221	1

Table 2(d). Descriptive statistics of spot and futures returns for silver.

	Silver Spot	Silver Fut1	Silver Fut3	Silver Fut6
Mean	$2.28x10^{-5}$	$1.40x10^{-5}$	$1.68x10^{-5}$	$2.06x10^{-5}$
Std. Dev.	0.019238	0.018253	0.018212	0.018180
Skewness	-0.621259	-1.005469	-1.015732	-1.021244
Kurtosis	15.93019	11.44866	11.47362	11.54257
Jarque-Bera	17717.02	7919.490	7972.545	8100.464
Correlation Matrix				
Silver Spot	1			
Silver Fut1	0.431762	1		
Silver Fut3	0.431766	0.999014	1	
Silver Fut6	0.432390	0.999448	0.999368	1

Table 2(e). Descriptive statistics of spot and futures returns for DAX30.

	DAX30 Spot	DAX30 Fut1	DAX30 Fut2
Mean	0.000310	0.000310	0.000309
Std. Dev.	0.011955	0.011892	0.011888
Skewness	-0.310123	-0.316872	-0.308995
Kurtosis	5.728112	5.690599	5.742054
Jarque-Bera	814.6914	795.2958	822.3388
Correlation Matrix			
DAX30 Spot	1		
DAX30 Fut1	0.987603	1	
DAX30 Fut2	0.990048	0.997221	1

Table 2(f). Descriptive statistics of spot and futures returns for CAC40.

	CAC40 Spot	CAC40 Fut1	CAC40 Fut2
Mean	0.000148	0.000166	0.000165
Std. Dev.	0.012219	0.012795	0.012718
Skewness	-0.177091	-0.173506	-0.198554
Kurtosis	7.272531	8.133110	8.047497
Jarque-Bera	1931.428	2781.475	2693.803
Correlation Matrix			
CAC40 Spot	1		
CAC40 Fut1	0.965606	1	
CAC40 Fut2	0.974066	0.976135	1

Table 2(g). Descriptive statistics of spot and futures returns for SP500.

	SP500 Spot	SP500 Fut1	SP500 Fut2	SP500 Fut3
Mean	0.000403	0.000404	0.000406	0.000408
Std. Dev.	0.009369	0.009535	0.009548	0.009587
Skewness	-0.492081	-0.580276	-0.547936	-0.553805
Kurtosis	7.532677	8.513357	8.423299	8.416488
Jarque-Bera	2223.086	3280.212	3163.355	3158.389
Correlation Matrix				
SP500 Spot	1			
SP500 Fut1	0.979376	1		
SP500 Fut2	0.980515	0.992921	1	
SP500 Fut3	0.980628	0.992786	0.999950	1

Table 2(h). Descriptive statistics of spot and futures returns for Nasdaq100.

	Nasdaq Spot	Nasdaq Fut1	Nasdaq Fut2
Mean	0.000588	0.000588	0.000590
Std. Dev.	0.010933	0.010920	0.010938
Skewness	-0.385396	-0.436000	-0.398398
Kurtosis	6.089037	6.715147	6.506768
Jarque-Bera	1056.284	1517.555	1347.654
Correlation Matrix			
Nasdaq Spot	1		
Nasdaq Fut1	0.969921	1	
Nasdaq Fut2	0.971849	0.983800	1

2.2 METHODOLOGY

The data were tested for stationarity and co-integration as a preliminary step for the Granger causality process.

2.2.1 Stationarity

The series stationarity was examined with the Augmented Dickey-Fuller (ADF) test for unit roots (Dickey and Fuller, 1979) and the Kwiatkovski-Phillips-Schmidt-Shin (KPSS) stationarity test (Kwiatkovski et al., 1992). Concisely, the ADF is based on the autoregressive model:

$$\Delta Y_t=\mu+\alpha t+\varphi Y_{t-1}+\sum_{i=1}^{p}\{\beta i \Delta Y(t-i)\}+e_t \qquad t=1,2,\ldots,n \qquad e_t\sim(0, \sigma^2)$$

The area of interest is coefficient φ. The null hypothesis that the series contains a unit root examines whether $\varphi=0$, against the alternative hypothesis that the series does not contain a unit root ($\varphi<0$).

The KPSS test breaks down the series into three components; a deterministic trend, a random walk and an error term. The test is based on the model:

$$Y_t=\xi t+r_t+e_t \qquad e_t\sim(0, \sigma^2)$$

where $r_t=r_{t-1}+u_t$ $u_t\sim(0, \sigma_u^2)$, a random walk process. The test uses the LM one-sided statistic for the stationarity hypothesis that $\sigma_u^2=0$.

If a (stochastically) non-stationary series Y_t requires differencing d times until it becomes stationary, Y_t is defined as integrated of order d, that is $Y_t\sim I(d)$ or $\Delta^d Y_t=I(0)$, where Δ^d is the difference operator Δ applied d times.

2.2.2 Co-Integration

Loosely speaking, two or more non-stationary time series are co-integrated if they do not drift apart from each other too much and maintain an equilibrium relationship. More precisely, if the components-series of the vector Y_t are in equilibrium, the following linear equation applies:

$$A^T Y_t=0$$

where A^T is the transpose of vector A. However, practically there is an equilibrium error equal to:

$z_t = A^T Y_t$, which can be interpreted as a temporary deviation from the equilibrium.

According to Engle and Granger (1987), co-integration of order (d,b) among the series of the vector Y_t, that is $Y_t \sim CI(d,b)$, exists if:

a) All series of vector Y_t are I(d), d>0 and

b) At least one vector $A \neq 0$ exists so that $z_t = A^T Y_t$ is I(d-b), $d \geq b > 0$. The vector A is the co-integrating vector.

Economic theory and non-arbitrage conditions suggest that spot and futures prices should be co-integrated and maintain an equilibrium relationship, although temporary financial forces may disengage the pair in the short term.

Co-integration was tested with the Johansen approach (Johansen, 1988). Let a set of n variables, (n>1) be I(1) and be depicted by the vector autoregressive model with k lags (in compact form):

$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_k Y_{t-k} + e_t$,

or in first differences:

$\Delta Y_t = \Pi Y_{t-k} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \ldots + \Gamma_{k-1} \Delta Y_{t-(k-1)} + e_t$

where Y_t is the nx1 vector of variables and Π, B_i and Γ_i are nxn matrices of coefficients. The area of interest is matrix Π whose rank r determines whether co-integration exists among the variables as well as the number of co-integrating vectors among the variables. Matrix Π consists of the possible co-integrating vectors multiplied by the ''weight'' with which each vector participates in the model, hence $\Pi = \alpha \beta^T$, where α (nxr) contains the ''weights'' and β (nxr) contains the co-integrating vectors. The rank of Π is determined by its eigenvalues (its characteristic roots different from zero). Let $\lambda_1, \lambda_2, \ldots, \lambda_n$ be the roots of Π in descending order, $\lambda_i \mathcal{E} [0,1]$. The Johansen co-integration method investigates the number of λs statistically different from zero. Two tests are used for the eigenvalues:

a) $\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \lambda i)$

b) $\lambda_{max}(r, r+1) = -T\ln(1 - \lambda_{r+1})$

The λ_{trace} (joint) test examines the null hypothesis that the number of co-integrating vectors are equal or less than r. It starts with r=0 (no co-integration) and successively investigates for higher number of vectors if the null hypothesis is not accepted. The λ_{max} test examines each eigenvalue under the null hypothesis that there are r co-integrating vectors, with the existence of r+1 vectors being the alternative hypothesis. Again, this is done consecutively.

2.2.3 Granger Causality

The concept of Granger causality, firstly introduced by Wiener (1956) and Granger (1969) suggests that for two stationary time series, let them be Y_t and X_t, X_t Granger causes Y_t if past values of X_t and incorporated information in them can be used to predict the future values of Y_t. Mathematically Granger non-causality implies that:

$$(Y_{t+1}, Y_{t+2},\ldots,Y_{t+k})|(F_{Xt},F_{Yt}) \sim (Y_{t+1}, Y_{t+2},\ldots,Y_{t+k})|(F_{Yt}) \qquad k\geq 1$$

where F_{Xt} and F_{Yt} denote the information sets available in series X_t and Y_t respectively until time t. In a more tangible way, Guidolin and Pedio (2018) involve the mean squared forecast errors (MSFE) in the definition of Granger non-causality:

$$MSFE(E[Y_t|Y_{t-1}, Y_{t-2},\ldots,Y_{t-\lambda} ,X_{t-1}, X_{t-2},\ldots X_{t-\lambda}]) = MSFE(E[Y_t|Y_{t-1}, Y_{t-2},\ldots,Y_{t-\lambda}]) \qquad \lambda\geq 1$$

where E denotes the expected value.

Granger causality was tested both linearly and non-linearly, with the VAR/VEC modelling and the Diks and Panchenko (2006) approach respectively.

2.2.3.1 Linear Granger Causality

In literature, the conventional way to test for Granger causality between two or more series involves the VAR modelling process. Particularly for the case of spot and futures prices the bivariate VAR model is:

$$S_t=\alpha_1+\sum_{i=1}^{k}(\beta_{1i}S_{t-i})+ \sum_{i=1}^{k}(\gamma_{1i}F_{t-i})+e_{1t}$$

$$F_t=\alpha_2+\sum_{i=1}^{k}(\beta_{2i}S_{t-i})+ \sum_{i=1}^{k}(\gamma_{2i}F_{t-i})+e_{2t}$$

where S_t and F_t are the spot and futures prices in log form, k is the optimal number of lags for the model and e_{1t} and e_{2t} supposedly uncorrelated white noise errors. Granger non-causality from F_t *(S_t)* to S_t *(F_t)* examines the null hypothesis that the coefficients γ_{1i} *(β_{2i})* are jointly equal to zero (a Wald type test) versus the alternative hypothesis that the coefficients γ_{1i} *(β_{2i})* are jointly non-zero. Actually, if no causality is proven, the bivariate VAR model collapses to two separate univariate models.

The model should involve stationary variables only, thus if S_t and F_t are non-stationary, the first differences ΔS_t and ΔF_t (returns) are used instead. In case S_t and F_t are non-stationary and also co-integrated (the most anticipated scenario based on the cost of carry theory), an error correction term (ECT) should be included in the model to account for the long-run equilibrium between the spot and futures prices. More precisely, ECT can be interpreted as long-term mispricing or distortion of the law of one price. In this way, any deviation in the short-run is supposedly ''corrected'' in the long-run and this effect is accounted for in the modelling process. The new ECT model (VECM) becomes:

$$\Delta S_t=\alpha_1+ \delta_1 ECT+\sum_{i=1}^{k}(\beta_{1i}\Delta S_{t-i})+ \sum_{i=1}^{k}(\gamma_{1i}\Delta F_{t-i})+e_{1t}$$

$$\Delta F_t=\alpha_2+\delta_2 ECT+\sum_{i=1}^{k}(\beta_{2i}\Delta S_{t-i})+ \sum_{i=1}^{k}(\gamma_{2i}\Delta F_{t-i})+e_{2t}$$

where ECT is a linear combination (at time t-1) of S_t and F_t indicated by their co-integrating vector (though S_t and F_t are non-stationary, the particular combination should be stationary, hence it can be used in the model) and δ_1 and δ_2 are the corresponding coefficients which can be interpreted as the speed of adjustment of S_t and F_t respectively to their long-run relationship once this has been ''violated''. Theoretically, at least one of δ_1 and δ_2 should be non-zero, i.e. $|\delta_1|+|\delta_2|>0$.

For each asset, linear dynamics were examined in pairs (spot with each corresponding futures contract separately) and altogether (spot with all corresponding futures contracts) using the suitable VAR/VECM. The optimal number of lags for each model was decided by the Schwarz information criterion (SIC). The VAR/VECM filtered residuals were also tested for Granger causality in the same way to ensure that any linear causal effects were revealed entirely.

2.2.3.2 Non-Linear Granger Causality

Although VAR and VEC models can detect the presence of linear causality, they fail to capture possible non-linear dynamics. Non-linear causality was investigated with the Diks and Panchenko (2006) non-parametric test which is considered an improvement over the efforts of Baek and Brock (1992) and Hiemstra and Jones (1994). In a non-parametric and finite framework, Granger non-causality can be restated as:

$Y_{t+1}|(X_t^{\lambda x} ; Y_t^{\lambda y}) \sim Y_{t+1}|(Y_t^{\lambda y})$

where $X_t^{\lambda x} = [X_{t-\lambda x+1},\ldots,X_t]$ and $Y_t^{\lambda y} = =[Y_{t-\lambda y+1},\ldots,Y_t]$.

The test regards time series as dynamical systems depicted as vectors in a lagged phase space with $\lambda_x=\lambda_y$. Dropping down time index, considering $\lambda_x=\lambda_y=1$ for simplicity and also given $Z=[Y_{t+1}]$, Granger non-causality can also be restated in terms of joint distributions as:

$F_{X,Z|Y}(x,z|y)=F_{X|Y}(x,y)F_{Z|Y}(z|y)$, or

$F_{X,Y,Z}(x,y,z)/F_{X,Y}(x,y)=F_{Y,Z}(y,z)/F_Y(y)$

where F denotes the probability density function. The two above equations imply that X and Z are independent conditionally on Y, or that X has no effect on the distribution of Z conditionally on Y. Diks and Panchenko (2006) demonstrated that the Granger non-causality null hypothesis implies that:

$q \equiv E[F_{X,Y,Z}(X,Y,Z)\ F_Y(Y) - F_{X,Y}(X,Y)\ F_{Y,Z}(Y,Z)]=0$

Let $\hat{F}_W(W_i)$ be a local density estimator of a d_w-variate random vector W=[X, Y, Z] at W_i defined by $\hat{F}_W(W_i)=(2\varepsilon_n)^{-dw}(n-1)^{-1}\boldsymbol{\Sigma}_{jj\neq i}I_{ij}^W$ where $I_{ij}^W=I(||W_i-W_j||<\varepsilon_n)$ with $I(\cdot)$ the indicator function and ε_n the bandwidth depending on the sample size n.

The test statistic for q concludes to:

$$T_{n(\varepsilon)} = \frac{n-1}{n(n-2)}\,\Sigma_i(\hat{F}_{X,Y,Z}(X_i,Y_i,Z_i)\ \hat{F}_Y(Y) - \hat{F}_{X,Y}(X_i,Y_i)\ \hat{F}_{Y,Z}(Y_i,Z_i))$$

For one lag $\lambda_X=\lambda_Y=1$ and bandwidth $\varepsilon=Cn^{-\beta}$ ($C>0$ and $0.25<\beta<0.\overline{3}$), $T_{n(\varepsilon)}$ satisfies:

$$n^{0.5}[(T_{n(\varepsilon)}-q)/S_n] \xrightarrow{x} N(0,1)$$

where $\xrightarrow{x}$ denotes convergence in distribution and S_n is the estimator of the asymptotic variance of $T_{n(\cdot)}$.

For constants C and β the optimal values suggested by the authors are C=8 (asymptotically) and β=2/7. Bandwidth ε was set to 0.96 corresponding to a sample of 2500 observations. The test was conducted for five different embedding dimensions (2 to 6).

In order to ensure that any causal dynamics detected by the Diks and Panchenko (2006) approach are non-linear in nature, the test was applied to the VAR/VECM filtered residuals supposedly purified from further linear causal effects.

2.3 RESULTS

2.3.1 Stationarity Results

Following the first step of the preliminary analysis, series stationarity was examined with the ADF and KPSS tests. Results are shown in table 3. WTI oil, gold, silver and DAX30 were found to be I(1) processes by both tests, while there are contradictions for natural gas, CAC40, SP500 and Nasdaq100. The ADF test finds low evidence of a unit root in the log series of those assets, whereas the KPSS test finds strong proof that the series are not stationary in levels.

Regarding those contradictory results, priority was given to the KPSS test results as the academic literature has already proven the low power of the ADF test under certain circumstances. Schwert (1987) tested macroeconomic series with unit roots and concluded that the Dickey-Fuller critical values are misleading. He opposed the argument that unit roots drive the asymptotic behavior of the model for large finite samples. Additionally, Schwert (1989) found that the ADF test is sensitive to the assumption that the variable under examination truly follows an AR(q) process. Given the fact that many economic series follow a mixed ARIMA process instead, the ADF test can be inaccurate. Agiakoglou and Newbond (1992) also showed that the ADF test rejects the null too often when a significant moving average component is included. Seo (1999) argued that, in the presence of conditional heteroskedasticity, the ADF test performs poorly and suggested that alternative unit root tests incorporating GARCH effects be used. Valkanov (2005) found that heteroskedasticity in data slows down the convergence in asymptotic distribution used to provide the DF critical values under the Functional CLT, even with sample sizes well above those used in this work, resulting in overrejection of the null. Hence, all series were treated as I(1) processes.

*Table 3. The ADF unit root test and the KPSS stationarity test results. <u>The first column</u> presents the asset under consideration (series in log-levels). <u>The second column</u> shows the p-values of the ADF test (null hypothesis: the series has a unit root). In parentheses, the p-values of the returns (log-first differences) are given. <u>The third column</u> presents the LM statistics of the KPSS test (null hypothesis: the series is stationary), with and without trend. In parentheses, the LM stat of the returns (log-first differences) are given. For both tests, *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively.*

Table 3. The ADF and KPSS results

Log-Series	ADF p-value	KPSS LM-stat {with trend/without trend}
WTI oil		
Spot	0.5108 (0.0000***)	0.553*** (0.072)/3.396*** (0.072)
Fut1	0.5030 (0.0000***)	0.555*** (0.072)/3.430*** (0.072)
Fut2	0.4955 (0.0000***)	0.558*** (0.073)/3.562*** (0.073)
Fut3	0.4875 (0.0000***)	0.561*** (0.074)/3.687*** (0.074)
Fut6	0.4585 (0.0000***)	0.568*** (0.072)/3.998*** (0.073)
Natural gas		
Spot	0.0335** (0.0000***)	0.215** (0.026)/1.902*** (0.049)
Fut1	0.0399** (0.0000***)	0.207** (0.030)/2.194*** (0.060)
Fut2	0.0565* (0.0000***)	0.201** (0.032)/2.412*** (0.066)
Fut3	0.0627* (0.0000***)	0.198** (0.032)/2.655*** (0.063)
Fut6	0.0740* (0.0000***)	0.190** (0.042)/3.540*** (0.054)
Gold		
Spot	0.2736 (0.0000***)	0.532*** (0.142)/1.425*** (0.144)
Fut1	0.2563 (0.0000***)	0.533*** (0.134)/1.436*** (0.135)
Fut2	0.2599 (0.0000***)	0.535*** (0.135)/1.414*** (0.136)
Fut3	0.2606 (0.0000***)	0.538*** (0.135)/1.386*** (0.136)
Fut6	0.2618 (0.0000***)	0.549*** (0.134)/1.295*** (0.135)
Silver		
Spot	0.3131 (0.0000***)	0.430*** (0.124)/3.622*** (0.143)
Fut1	0.2717 (0.0000***)	0.429*** (0.119)/3.636*** (0.137)
Fut3	0.2743 (0.0000***)	0.432*** (0.119)/3.605*** (0.136)
Fut6	0.2756 (0.0000***)	0.435*** (0.119)/3.544*** (0.135)
DAX30		
Spot	0.1627 (0.0000***)	0.547*** (0.029)/5.642*** (0.034)
Fut1	0.1643 (0.0000***)	0.546*** (0.028)/5.638*** (0.034)
Fut2	0.1633 (0.0000***)	0.546*** (0.028)/5.632*** (0.034)
CAC40		
Spot	0.0321** (0.0000***)	0.296*** (0.037)/5.076*** (0.077)
Fut1	0.0384** (0.0000***)	0.298*** (0.043)/5.213*** (0.075)
Fut2	0.0382** (0.0000***)	0.300*** (0.044)/5.183*** (0.076)

(to be continued…)

(...continued)

SP500		
Spot	0.0308** (0.0000***)	0.431*** (0.023)/5.990*** (0.023)
Fut1	0.0291** (0.0000***)	0.418*** (0.023)/5.990*** (0.022)
Fut2	0.0260** (0.0000***)	0.396*** (0.023)/5.991*** (0.023)
Fut3	0.0246** (0.0000***)	0.376*** (0.023)/5.993*** (0.022)
Nasdaq100		
Spot	0.0006*** (0.0000***)	0.149** (0.018)/6.119*** (0.019)
Fut1	0.0007*** (0.0000***)	0.146** (0.018)/6.119*** (0.020)
Fut2	0.0007*** (0.0000***)	0.144* (0.018)/6.119*** (0.020)

2.3.2 Co-integration Results

The results of Johansen co-integration are presented in table 4. All combinations were found to be co-integrated at 5% level of significance, except for the pair of spot-futures contract 6 for WTI oil and the pair of spot-futures contract 2 for CAC40. Results are consistent for both λ_{trace} and λ_{max} tests.

*Table 4. The Johansen co-integration results. The first column presents the combination of variables examined for co-integration (pairwise and altogether). The second column shows the null hypotheses for the number of co-integrating vectors and particularly the last one not to be accepted and the first one to be accepted (in bold the number of co-integrating vectors indicated by the two statistics-see next columns). The third column shows the trace statistic of the λ_{trace} test and its p-value in parenthesis. The fourth column shows the max. eigenvalue statistic of the λ_{max} test and its p-value in parenthesis. *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The 5% significance level was considered to determine the number of vectors for the next steps.*

Table 4. The Johansen co-integration results

Variables	Null hypothesis	Trace statistic	Max eigenvalue statistic
WTI oil			
Spot-futures 1	None	301.540 (0.0001)***	230.717 (0.0001)***
	At most one	2.277 (0.1313)	2.277 (0.1313)
Spot-futures 2	None	51.193 (0.0000)***	48.970 (0.000)***
	At most one	2.222 (0.1360)	2.223 (0.1360)

(to be continued...)

(…continued)

Spot-futures 3	None	25.734 (0.0010)***	23.621 (0.0013)***
	At most one	2.114 (0.1460)	2.114 (0.1460)
Spot-futures 6	**None**	14.058 (0.0814)*	12.185 (0.1039)
	At most one	1.873 (0.1711)	1.873 (0.1711)
Spot-futures 1-2-3-6	At most two	73.167 (0.0000)***	61.207 (0.0000)***
	At most three	11.960 (0.1589)	10.214 (0.1982)
Natural gas			
Spot-futures 1	None	326.904 (0.0001)***	316.269 (0.0001)***
	At most one[1]	10.634 (0.0011)***	10.634 (0.0011)***
Spot-futures 2	None	72.283 (0.0000)***	63.699 (0.0000)***
	At most one[1]	8.585 (0.0034)***	8.585 (0.0034)***
Spot futures 3	None	53.496 (0.0000)***	45.542 (0.0000)***
	At most one[1]	7.953 (0.0048)***	7.953 (0.0048)***
Spot-futures 6	None	27.699 (0.0005)***	23.778 (0.0012)***
	At most one[1]	3.921 (0.0477)**	3.921 (0.0477)**
Spot-futures 1-2-3-6	At most three	23.493 (0.0025)***	18.214 (0.0113)**
	At most four[1]	5.279 (0.0216)**	5.279 (0.0216)**
Gold			
Spot-futures 1	None	541.684 (0.0001)***	537.876 (0.0001)***
	At most one	3.808 (0.0510)*	3.808 (0.0510)*
Spot-futures 2	None	493.963 (0.0001)***	490.179 (0.0001)***
	At most one	3.784 (0.0517)*	3.784 (0.0517)*
Spot futures 3	None	188.531 (0.0001)***	184.884 (0.0001)***
	At most one	3.647 (0.0562)*	3.647 (0.0562)*
Spot-futures 6	None	24.960 (0.0014)***	21.151 (0.0035)***
	At most one	3.809 (0.0510)*	3.809 (0.0510)*
Spot-futures 1-2-3-6	At most two	68.445 (0.0000)***	63.124 (0.0000)***
	At most three	5.321 (0.7739)	4.066 (0.8523)
Silver			
Spot-futures 1	None	739.514 (0.0001)***	737.307 (0.0001)***
	At most one	2.207 (0.1374)	2.207 (0.1374)
Spot futures 3	None	659.891 (0.0001)***	657.663 (0.0001)***
	At most one	2.229 (0.1355)	2.229 (0.1355)
Spot-futures 6	None	95.087 (0.0001)***	92.831 (0.0001)***
	At most one	2.255 (0.1331)	2.255 (0.1331)
Spot-futures 1-3-6	At most one	52.390 (0.0000)***	44.546 (0.0000)***
	At most two	7.844 (0.4822)	6.816 (0.5111)
DAX30			
Spot-futures 1	None	229.595 (0.0001)***	227.905 (0.0001)***
	At most one	1.690 (0.1936)	1.690 (0.1936)
Spot-futures 2	None	46.428 (0.0000)***	45.054 (0.0000)***
	At most one	1.374 (0.2411)	1.374 (0.2411)
Spot-futures 1-2	At most one	38.037 (0.0000)***	36.408 (0.0000)***
	At most two	1.629 (0.2019)	1.629 (0.2019)

(to be continued…)

(…continued)

CAC40

Spot-futures 1	None	23.028 (0.0030)***	21.483 (0.0031)***
	At most one	1.545 (0.2139)	1.545 (0.2139)
Spot-futures 2	**None**	14.560 (0.0688)*	13.021 (0.0778)*
	At most one	1.539 (0.2147)	1.539 (0.2147)
Spot-futures 1-2	At most one	16.317 (0.0375)**	14.749 (0.0419)**
	At most two	1.568 (0.2105)	1.568 (0.2105)

SP500

Spot-futures 1	None	162.183 (0.0001)***	161.770 (0.0001)***
	At most one	0.412 (0.5209)	0.412 (0.5209)
Spot-futures 2	None	59.372 (0.0000)***	58.963 (0.0000)***
	At most one	0.409 (0.5226)	0.409 (0.5226)
Spot futures 3	None	22.433 (0.0038)***	22.015 (0.0025)***
	At most one	0.418 (0.5178)	0.418 (0.5178)
Spot-futures 1-2-3	At most one	217.320 (0.0001)***	211.972 (0.0001)***
	At most two	5.348 (0.7708)	4.453 (0.8087)

Nasdaq100

Spot-futures 1	None	265.959 (0.0001)***	265.746 (0.0001)***
	At most one	0.213 (0.6445)	0.213 (0.6445)
Spot-futures 2	None	64.360 (0.0000)***	64.147 (0.0000)***
	At most one	0.213 (0.6447)	0.213 (0.6447)
Spot-futures 1-2	At most one	58.443 (0.0000)***	58.202 (0.0000)***
	At most two	0.242 (0.6230)	0.242 (0.6230)

[1] *For natural gas, the test indicates two co-integrating vectors for pairs and five vectors for the set of five. Since this is not possible, the maximum numbers of vectors were chosen (n-1 for a combination of n variables).*

2.3.3 Granger Causality Results

For better comprehension and evaluation, causality results are classified and presented by asset, merging the linear and non-linear approaches.

WTI oil. Table 5(a) shows the models used for the four pairs of spot and futures contracts for WTI oil. The coefficients of the ECT are significant in all spot equations, but not in the futures ones, implying that it is the spot price that ''strives'' to maintain the equilibrium with the futures and that there is long-run lead of futures market. The coefficients are also negative, an anticipated fact considering that the co-integrating vectors are normalized on the spot variable. The coefficients of the first lag of spot and futures appear to be significant for almost all pairs and equations, while earlier lags seem to affect primarily the spot equations. In the multivariate 5x5 model, shown in table 5(b), the spot price follows the equilibrium determined by the ECT1, while both spot and futures remain inactive concerning the other two co-integrating relationships. Almost all lags, except for the first lag of the six-month futures contract, are independently insignificant in this model.

Regarding, short-run causal effects, table 5(c) presents the linear and non-linear results of the corresponding tests. The VAR/VEC modelling revealed that the spot Granger-causes the first and last futures contracts, but there is a feedback mechanism between spot and the contracts of the second and third months. It is notable that the p-value of the front month is close to the threshold of 10% significance level and the p-value of the last contract is close to the threshold of 5%. The multivariate 5x5 model discovered bi-directional causality between spot and the last futures and notably weakened any causal effects between spot and earlier contracts. Residuals of linear modelling showed no further linear effects, as expected. Under the non-linear framework, there is strong and consistent evidence that futures of all maturities Granger-cause the spot market. For the second and third embedding dimensions, spot also Granger-causes the futures contracts of all maturities, but the effects are not persistent throughout all lags reported. An exception to that pattern of non-linear channels is the bidirectional non-linear relationship of spot and front month contract.

*Table 5(a) and Table 5(b) (see next page). The coefficient results of the VAR/VEC models for WTI oil. Table 5(a) shows the results of the bivariate models (pairwise) and table 5(b) (next page) shows the results of the multivariate (5x5) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 5(a) WTI Oil (pairwise)

Model/Dependent Variables		c	ECT_{t-1}[1] (coint. eq.)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogFut_{t-1}$	$DlogFut_{t-2}$	$DlogFut_{t-3}$
VECM	DlogSpot	-0.000158	-0.336584***	-0.070355	-0.117189*	-0.134337**	0.028976	0.114726	0.133846**
	DlogFut1	-0.000158	0.008826	0.160453**	0.066728	-0.061549	-0.212541***	-0.064378	0.057734
VECM	DlogSpot	-0.000152	-0.102512***	-0.205443***	-0.229279***	-0.199036***	0.170618***	0.240915***	0.209759***
	DlogFut2	-0.000162	-0.031886	0.172949***	0.055930	-0.050631	-0.242960***	-0.049227	0.047465
VECM	DlogSpot	-0.000148	-0.050117***	-0.189051***	-0.207769***	-0.178663***	0.158056***	0.224531***	0.193642***
	DlogFut3	-0.000167	-0.017865	0.153694***	0.053773	-0.042960	-0.227879***	-0.043868	0.035894
VAR	DlogSpot	-0.000153	-	-0.102052**	-0.120510**	-	0.066047	0.135718**	-
	DlogFut6	-0.000188	-	0.139043***	0.054537	-	-0.227189***	-0.040526	-

[1.] *For spot-fut1 pair: ECT=logspot-1.005901logfut1+0.026442*

For spot-fut2 pair: ECT=logspot-1.025173logfut2+0.114800

For spot-fut3 pair: ECT=logspot-1.040424logfut3+0.184786

Table 5(b). Results of the multivariate (5x5) VEC model for WTI oil (see previous page for further description).

Table 5(b) WTI Oil (5x5)

Model/Dependent Variables		c	$ECT1_{t-1}$[1] (coint. eq.1)	$ECT2_{t-1}$[1] (coint. eq.2)	$ECT3_{t-1}$[1] (coint. eq.3)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogFut1_{t-1}$
	DlogSpot	-0.000177	-0.335138***	0.257475*	0.139117	-0.064302	-0.125973*	-0.136548**	-0.102496
	DlogFut1	-0.000181	0.091768	-0.271491*	0.159080	0.101828	0.005312	-0.080317	-0.324951*
VECM	DlogFut2	-0.000183	0.029153	0.059149	-0.511011	0.127164*	0.040933	-0.068340	-0.061324
	DlogFut3	-0.000184	0.009759	0.032238	-0.291090	0.135950*	0.059265	-0.062313	-0.107600
	DlogFut6	-0.000196	-0.008886	0.070022	-0.275385	0.135336*	0.066852	-0.066074	-0.114749

WTI Oil (5x5) *cont.*

Model/Dependent Variables	$DlogFut1_{t-2}$	$DlogFut1_{t-3}$	$DlogFut2_{t-1}$	$DlogFut2_{t-2}$	$DlogFut2_{t-3}$	$DlogFut3_{t-1}$	$DlogFut3_{t-2}$	$DlogFut3_{t-3}$
DlogSpot	-0.099513	-0.057804	0.091293	0.237850	0.134621	0.627030	-0.095214	0.408488
DlogFut1	-0.316148**	-0.048691	0.228634	0.342861	0.373321	0.688197	-0.175915	0.039862
DlogFut2	-0.150256	0.039884	-0.250062	0.088666	0.217353	0.761920	-0.064800	0.022370
DlogFut3	-0.189641	0.012559	0.015135	0.183250	0.233147	0.394122	-0.128058	0.009377
DlogFut6	-0.172083	0.010984	-0.049651	0.140157	0.183996	0.428833	-0.039626	0.073997

WTI Oil (5x5) *cont.*

Model/Dependent Variables	$DlogFut6_{t-1}$	$DlogFut6_{t-2}$	$DlogFut6_{t-3}$
DlogSpot	-0.642846***	0.092672	-0.364276
DlogFut1	-0.809217***	0.168675	-0.309555
DlogFut2	-0.694852***	0.101552	-0.235420
DlogFut3	-0.548010**	0.093568	-0.219204
DlogFut6	-0.500332**	0.024758	-0.229740

[1.] *ECT1=logspot-1.897142logfut3+0.893620logfut6+0.020444*

ECT2=logfut1-1.807262logfut3+0.805488logfut6+0.012328

ECT3=logfut2-1.401409logfut3+0.401260logfut6+0.002303

*Table 5(c). Causality results for WTI oil. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 5(c) Causality results for WTI oil

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.0291**	0.1191	0.8947	0.8907	2	0.00028***	0.00001***
					3	0.00121***	0.00041***
					4	0.00676***	0.00017***
					5	0.01635**	0.00324***
					6	0.03815**	0.01648**
Spot-Futures 2	0.0054***	0.0002***	0.7756	0.8867	2	0.00132***	0.00000***
					3	0.00767***	0.00004***
					4	0.06549*	0.00002***
					5	0.15680	0.00065***
					6	0.24560	0.00481***
Spot-Futures 3	0.0095***	0.0003***	0.7828	0.8684	2	0.00099***	0.00000***
					3	0.01349**	0.00001***
					4	0.13862	0.00001***
					5	0.34725	0.00023***
					6	0.42471	0.00318***
Spot-Futures 6	0.0037***	0.0513*	0.8889	0.6917	2	0.00400***	0.00000***
					3	0.04254**	0.00000***
					4	0.18439	0.00001***
					5	0.62957	0.00049***
					6	0.75907	0.00278***
Multivariate (5x5)							
Spot-Futures 1	0.1183	0.9215	0.8728	0.9904			
Spot-Futures 2	0.0760*	0.9232	0.8543	0.9419			
Spot-Futures 3	0.0548*	0.3785	0.8550	0.8831			
Spot-Futures 6	0.0257**	0.0242**	0.8533	0.8880			
Spot-Fut1,2,3,6	-	0.0674*	-	0.9998			

Natural gas. Table 6(a) presents the pairwise VEC models for natural gas. As in the case of oil, the coefficients of the ECT are negative and statistically significant in the spot equations indicating that the equilibrium relationship is maintained in the long run and any deviations are corrected by spot movements. For the pair of spot and the six-month contract, the coefficient of ECT is also negative and important in the futures equation, but smaller in absolute value than the coefficient in the spot equation (|-0.006310|<|-0.030335|), thus equilibrium perseveres in this pair as well. Almost all lags of spot and futures affect spot equations independently, but only the first lag of futures appears significant for futures equations. Interestingly however, spot and futures lags of eight and nine days are very significant for the front-month futures equation. In the multivariate 5x5 model, shown in table 6(b), both the spot and the earliest futures seem to correct any departures from the long-run relationships. Also, the fact that the coefficient of the ECT4 for the six-month contract is negative and significant seems abnormal as this implies that the contract ‘’tries’’ to break off the particular equilibrium.

Linear testing (table 6(c)) detected bidirectional causality between spot and one-month futures contract, but futures lead spot for longer maturities. The futures also dominate the spot jointly in the multivariate 5x5 model, but they are unable to Granger cause the spot market separately except for the front month contract. Additionally, VECM filtered residuals proved to be purified from further linear effects. Non-linear causal effects present the same pattern as the linear ones. In particular, bidirectional non-linear causality was detected between spot and the earliest contract for almost all embedding dimensions, while the futures of longer maturities consistently dominate the spot.

Table 6(a). Results of the bivariate VEC models for natural gas (see next page for further description).

Table 6(a) Natural Gas (pairwise)

Model/Dependent Variables		c	ECT $_{t-1}$[1] (coint. eq.)	DlogSpot$_{t-1}$	DlogSpot$_{t-2}$	DlogSpot$_{t-3}$	DlogSpot$_{t-4}$	DlogSpot$_{t-5}$	DlogSpot$_{t-6}$
VECM	DlogSpot	-0.000075	-0.158449***	-0.024468	-0.151325***	-0.091962***	-0.170280***	-0.086406***	-0.046833**
	DlogFut1	-0.000300	-0.001608	0.033265*	0.005566	-0.005741	0.018749	0.045679**	0.027167
VECM	DlogSpot	-0.000164	-0.090807***	-0.037572*	-0.178511***	-0.092172***	-0.174383***	-0.080405***	-
	DlogFut2	-0.000279	-0.003817	0.027043*	0.005243	-0.012171	0.014566	0.017288	-
VECM	DlogSpot	-0.000144	-0.063685***	-0.039800*	-0.191222***	-0.098508***	-0.176935***	-0.081297***	-
	DlogFut3	-0.000276	-0.001964	0.023550*	0.001144	-0.004191	0.014810	0.019903	-
VECM	DlogSpot	0.000074	-0.030335***	-0.051039**	-0.188069***	-0.099951***	-0.177838***	-0.079132***	-
	DlogFut6	-0.000368	-0.006310**	0.005602	-0.003750	-0.000134	0.012438	0.017992*	-

Natural Gas (pairwise) *cont.*

Model/Dependent Variables		DlogSpot$_{t-7}$	DlogSpot$_{t-8}$	DlogSpot$_{t-9}$	DlogFut$_{t-1}$	DlogFut$_{t-2}$	DlogFut$_{t-3}$	DlogFut$_{t-4}$	DlogFut$_{t-5}$
VECM	DlogSpot	-0.093329***	0.032209	0.058776***	0.453140***	0.107640***	0.090779***	0.118924***	0.161551***
	DlogFut1	0.029025*	0.051852***	0.041359***	-0.074954***	-0.032388	0.002751	-0.021449	-0.047408*
VECM	DlogSpot	-	-	-	0.521873***	0.160431***	0.149225***	0.109150***	0.185237***
	DlogFut2	-	-	-	-0.086945***	-0.035844	0.005965	-0.022122	-0.016768
VECM	DlogSpot	-	-	-	0.549819***	0.172850***	0.190745***	0.141176***	0.180158***
	DlogFut3	-	-	-	-0.072871***	-0.027777	0.003232	-0.031362	-0.005650
VECM	DlogSpot	-	-	-	0.717463***	0.227100***	0.204538***	0.227554***	0.198927***
	DlogFut6	-	-	-	-0.047187**	-0.001366	-0.026961	-0.014081	-0.009009

Natural Gas (pairwise) *cont.*

Model/Dependent Variables		DlogFut$_{t-6}$	DlogFut$_{t-7}$	DlogFut$_{t-8}$	DlogFut$_{t-9}$
VECM	DlogSpot	0.081454***	0.061690**	0.111578***	0.062315**
	DlogFut1	-0.020925	0.006261	-0.065728***	-0.081334***
VECM	DlogSpot	-	-	-	-
	DlogFut2	-	-	-	-
VECM	DlogSpot	-	-	-	-
	DlogFut3	-	-	-	-
VECM	DlogSpot	-	-	-	-
	DlogFut6	-	-	-	-

[1]. For spot-fut1 pair: ECT=logspot-1.019233logfut1+0.024573
For spot-fut2 pair: ECT=logspot-1.041058logfut2+0.067192
For spot-fut3 pair: ECT=logspot-1.043513logfut3+0.086875
For spot-fut6 pair: ECT=logspot-0.899714logfut6-0.057628

*Table 6(a) (see previous page) and Table 6(b). The coefficient results of the VAR/VEC models for natural gas. Table 6(a) (previous page) shows the results of the bivariate models (pairwise) and table 6(b) shows the results of the multivariate (5x5) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 6(b) Natural Gas (5x5)

Model/Dependent Variables		c	$ECT1_{t-1}$[1] (coint. eq.1)	$ECT2_{t-1}$[1] (coint. eq.2)	$ECT3_{t-1}$[1] (coint. eq.3)	$ECT4_{t-1}$[1] (coint. eq.4)	$DlogSpot_{t-1}$	$DlogFut1_{t-1}$	$DlogFut2_{t-1}$
	DlogSpot	-0.000164	-0.286627***	0.541743***	-0.359300***	0.114656***	0.092042***	0.212060**	0.109355
	DlogFut1	-0.000292	0.030824***	-0.162472***	0.150155***	-0.035880	0.004339	0.034143	-0.267609**
VECM	DlogFut2	-0.000286	0.014615	-0.036484	-0.043889	0.054662*	0.011369	0.099510	-0.326889***
	DlogFut3	-0.000294	0.009870	-0.013800	-0.025882	0.010272	0.010816	0.088256	-0.167932*
	DlogFut6	-0.000379	-0.000965	-0.035066	0.069997*	-0.046177**	-0.000513	0.078326*	-0.176498**

Natural Gas (5x5) *cont.*

Model/Dependent Variables	$DlogFut3_{t-1}$	$DlogFut6_{t-1}$
DlogSpot	-0.017909	0.088706
DlogFut1	0.213549**	0.014169
DlogFut2	0.179037**	0.007502
DlogFut3	0.023836	0.005352
DlogFut6	0.090422	-0.030554

[1.] *ECT1=logspot-0.910303logfut6-0.044975*

ECT2=logfut1-0.908397logfut6-0.049349

ECT3=logfut2-0.898613logfut6-0.077738

ECT4=logfut3-0.902840logfut6-0.088573

*Table 6(c). Causality results for natural gas. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 6(c) Causality results for Natural Gas

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.0046***	0.0000***	0.9590	0.9916	2	0.00104***	0.00000***
					3	0.00026***	0.00001***
					4	0.00127***	0.00003***
					5	0.00407***	0.00120***
					6	0.10228	0.00589***
Spot-Futures 2	0.2176	0.0000***	0.9884	0.8015	2	0.46764	0.00000***
					3	0.07142*	0.00000***
					4	0.08334*	0.00001***
					5	0.07189*	0.00019***
					6	0.64942	0.00254***
Spot-Futures 3	0.2479	0.0000***	0.9964	0.8349	2	0.78862	0.00000***
					3	0.28255	0.00001***
					4	0.12124	0.00003***
					5	0.10186	0.00031***
					6	0.60729	0.00418***
Spot-Futures 6	0.3060	0.0000***	0.9263	0.8647	2	0.87304	0.00000***
					3	0.80935	0.00178***
					4	0.64444	0.00872***
					5	0.72698	0.03506**
					6	0.83583	0.15781
Multivariate (5x5)							
Spot-Futures 1	0.7683	0.0143**	0.7809	0.6926			
Spot-Futures 2	0.4006	0.4690	0.7392	0.7490			
Spot-Futures 3	0.3855	0.8738	0.7535	0.8869			
Spot-Futures 6	0.9572	0.2025	0.7380	0.9370			
Spot-Fut1,2,3,6	-	0.0000***	-	0.9967			

Gold. Results for pairwise models for gold are presented in table 7(a). The coefficients of the ECT are negative and significant in the spot equations, implying that it is the spot which reacts to departures from the long-run relationship with the corresponding futures. The coefficients of almost all lags of spot and futures imply that those lags significantly affect spot equations, while they have very little influence on futures equations. Equilibrium is also stabilized by the spot market in the multivariate 5x5 model (table 7(b)). In the multivariate context, futures lags do not affect much the spot which is now affected more by its own lags only. Also, the second and fourth lags of the second contract and the second lag of the third contract now influence futures current values.

Concerning Granger causality dynamics (table 7(c)), there is very strong evidence of futures linear dominance over the spot market in pairwise models, but this lead is completely lost in the multivariate 5x5 model. Once again, there were no causal dynamics detected in the VECM filtered residuals. Regarding non-linear dynamics, there is consistent evidence at 5% significance level that futures of all maturities drive the spot market, though this evidence weakens for the last embedding dimension included in the test. The non-linear channels from spot to futures are very inconsistent and it is concluded that they can be disregarded.

Table 7(a). Results of the bivariate VEC models for gold (see next page for further description).

Table 7(a) Gold (pairwise)

Model/Dependent Variables		c	ECT_{t-1}[1] (coint. eq.)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$	$DlogSpot_{t-6}$
VECM	DlogSpot	0.000108	-0.637714***	-0.292516***	-0.273225***	-0.235674***	-0.210864***	-0.176097***	-0.103775***
	DlogFut1	0.000107	0.100150	-0.092949	-0.100412	-0.125395	-0.066199	-0.067704	-0.043085
VECM	DlogSpot	0.000099	-0.541039***	-0.377304***	-0.345824***	-0.297815***	-0.260367***	-0.211259***	-0.127454***
	DlogFut2	0.000109	0.085362	-0.079854	-0.087327	-0.116195	-0.060190	-0.060622	-0.037300
VECM	DlogSpot	0.000077	-0.312926***	-0.573714***	-0.513469***	-0.436424***	-0.370578***	-0.294082***	-0.183362***
	DlogFut3	0.000113	0.042936	-0.037680	-0.050145	-0.084380	-0.033966	-0.040687	-0.023008
VECM	DlogSpot	0.000048	-0.070604***	-0.781805***	-0.688642***	-0.579998***	-0.485387***	-0.380522***	-0.243574***
	DlogFut6	0.000118	0.006567	-0.005133	-0.019888	-0.054761	-0.008423	-0.020379	-0.011288

Gold (pairwise) *cont.*

Model/Dependent Variables		$DlogSpot_{t-7}$	$DlogSpot_{t-8}$	$DlogFut_{t-1}$	$DlogFut_{t-2}$	$DlogFut_{t-3}$	$DlogFut_{t-4}$	$DlogFut_{t-5}$	$DlogFut_{t-6}$
VECM	DlogSpot	-0.066580**	-0.008812	0.297111***	0.250910***	0.228445***	0.201784***	0.176927***	0.121509***
	DlogFut1	-0.002264	0.021514	0.063905	0.092556	0.116492	0.095724	0.066458	0.063140
VECM	DlogSpot	-0.079499***	-0.011580	0.389016***	0.331036***	0.297046***	0.259563***	0.221319***	0.153233***
	DlogFut2	0.001935	0.021884	0.050084	0.079621	0.105301	0.087850	0.059546	0.056327
VECM	DlogSpot	-0.109857***	-0.017064	0.603127***	0.514483***	0.453954***	0.388171***	0.323652***	0.229121***
	DlogFut3	0.011657	0.024960	0.008761	0.037918	0.070847	0.056855	0.035911	0.038345
VECM	DlogSpot	-0.145094***	-0.024317	0.831405***	0.710277***	0.617376***	0.522684***	0.429807***	0.307959***
	DlogFut6	0.015292	0.024855	-0.026670	0.007776	0.039974	0.028894	0.012132	0.020043

Gold (pairwise) *cont.*

Model/Dependent Variables		$DlogFut_{t-7}$	$DlogFut_{t-8}$
VECM	DlogSpot	0.090558***	
	DlogFut1	0.027371	
VECM	DlogSpot	0.111323***	0.043392*
	DlogFut2	0.020846	-0.017239
VECM	DlogSpot	0.161215***	0.067581***
	DlogFut3	0.007713	-0.025149
VECM	DlogSpot	0.216139***	0.095265***
	DlogFut6	0.000014	-0.027378

[1] For spot-fut1 pair: ECT=logspot-1.00647logfut1+0.004628
For spot-fut2 pair: ECT=logspot-0.999585logfut2-0.001774
For spot-fut3 pair: ECT=logspot-0.999739logfut3+0.001026
For spot-fut6 pair: ECT=logspot-1.004715logfut6-0.042342

*Table 7(a) (see previous page) and Table 7(b). The coefficient results of the VAR/VEC models for gold. Table 7(a) (previous page) shows the results of the bivariate models (pairwise) and table 7(b) shows the results of the multivariate (5x5) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 7(b) Gold (5x5)

Model/Dependent Variables		c	ECT1 $_{t-1}$[1] (coint. eq.1)	ECT2 $_{t-1}$[1] (coint. eq.2)	ECT3 $_{t-1}$[1] (coint. eq.3)	DlogSpot$_{t-1}$	DlogSpot$_{t-2}$	DlogSpot$_{t-3}$	DlogSpot$_{t-4}$
	DlogSpot	0.000122	-0.784359***	0.433357*	0.812852	-0.141994***	-0.116023***	-0.070740**	-0.037388**
	DlogFut1	0.000126	0.045870	0.022970	-0.042867	-0.038522	-0.034796	-0.059048	0.001004
VECM	DlogFut2	0.000128	0.042095	0.133575	-0.265112	-0.036109	-0.031661	-0.058015	0.000095
	DlogFut3	0.000129	0.040875	0.119150	-0.170392	-0.034604	-0.031215	-0.058616	-0.000498
	DlogFut6	0.000131	0.041362	0.103193	-0.176792	-0.036103	-0.033012	-0.058182	0.000313

Gold (5x5) *cont.*

Model/Dependent Variables	DlogFut1$_{t-1}$	DlogFut1$_{t-2}$	DlogFut1$_{t-3}$	DlogFut1$_{t-4}$	DlogFut2$_{t-1}$	DlogFut2$_{t-2}$	DlogFut2$_{t-3}$	DlogFut2$_{t-4}$
DlogSpot	0.014967	-0.014621	0.120661	-0.248138	-0.175503	0.807389	-0.017337	0.467831
DlogFut1	-0.386276	-0.022563	-0.177640	-0.120221	1.402715	2.707103**	1.346325	2.380206*
DlogFut2	-0.311594	-0.069997	-0.197988	-0.128289	1.352510	2.748874**	1.388583	2.512783**
DlogFut3	-0.333864	-0.073787	-0.220909	-0.152773	1.742998	2.955744**	1.517232	2.536562**
DlogFut6	-0.365375	-0.046549	-0.202507	-0.136389	1.372626	2.718845**	1.452058	2.437124**

Gold (5x5) *cont.*

Model/Dependent Variables	DlogFut3$_{t-1}$	DlogFut3$_{t-2}$	DlogFut3$_{t-3}$	DlogFut3$_{t-4}$	DlogFut6$_{t-1}$	DlogFut6$_{t-2}$	DlogFut6$_{t-3}$	DlogFut6$_{t-4}$
DlogSpot	0.588899	-0.195359	0.208499	-0.070972	-0.278516	-0.499141	-0.242367	-0.114705
DlogFut1	-0.290584	-2.015478**	-0.731372	-1.162998	-0.718912	-0.639954	-0.384742	-1.071149
DlogFut2	-0.410573	-2.136997**	-0.813106	-1.227204	-0.626395	-0.514786	-0.326788	-1.131694
DlogFut3	-0.890737	-2.380079**	-0.971018	-1.310584	-0.515153	-0.476003	-0.274504	-1.047503
DlogFut6	-0.319516	-2.020198**	-0.738958	-1.184441	-0.683839	-0.624580	-0.459394	-1.091087

[1.] *ECT1=logspot-1.472989logfut3+0.475603logfut6-0.018521*

ECT2=logfut1-1.540438logfut3+0.543534logfut6-0.022336

ECT3=logfut2-1.303916logfut3+0.304971logfut6-0.007576

*Table 7(c). Causality results for gold. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 7(c) Causality results for Gold

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.7548	0.0009***	0.9474	0.9420	2	0.00021***	0.04489**
					3	0.01231**	0.01482**
					4	0.12948	0.04481**
					5	0.07811*	0.05444*
					6	0.02879**	0.20580
Spot-Futures 2	0.7807	0.0000***	0.9362	0.9196	2	0.00096***	0.02920**
					3	0.02025**	0.00507***
					4	0.15421	0.02650**
					5	0.12814	0.03013**
					6	0.04070**	0.11479
Spot-Futures 3	0.8274	0.0000***	0.9210	0.8463	2	0.00096***	0.02917**
					3	0.01932**	0.01025**
					4	0.12454	0.04355**
					5	0.06336*	0.04198**
					6	0.02107**	0.06007*
Spot-Futures 6	0.8918	0.0000***	0.9076	0.7482	2	0.00048***	0.01411**
					3	0.02587**	0.00380***
					4	0.07241*	0.03061**
					5	0.08388*	0.04882**
					6	0.03403**	0.08877*
Multivariate (5x5)							
Spot-Futures 1	0.6428	0.9792	0.9845	0.9303			
Spot-Futures 2	0.6570	0.8143	0.9812	0.9266			
Spot-Futures 3	0.6522	0.6286	0.9808	0.9896			
Spot-Futures 6	0.6580	0.8213	0.9834	0.9486			
Spot-Fut1,2,3,6	-	0.4967	-	1.0000			

Silver. Bivariate results for silver are shown in table 8(a). In the long-run, the spot market revises the equilibrium with futures as indicated by the ECT coefficients. Coefficients of almost all spot and futures lags suggest that they heavily influence spot equations independently, while they have much weaker effect on futures equations. In the multivariate 4x4 model (table 8(b)) it is the spot market again which reacts to deviations for the long-run relationships. As in the case of gold, in the multivariate context, futures lags independently lose their influence on spot which is now affected by its own previous values. Futures equations do not appear to be affected by any lag separately.

Moving on to the short-run linear causal dynamics (table8(c)), there is some evidence of the front month futures contract leading the spot, but there is much stronger evidence of the futures dominance for later maturities. As it happened with gold, this leading effect is completely lost when a multivariate 4x4 model is considered. Furthermore, the VECM filtered residuals proved to have been purified from any linear causal effects both in the bivariate and multivariate models. Regarding non-linear dynamics, futures of all maturities Granger-cause spot consistently for all embedding dimensions considered. There is some proof that the spot can predict the futures contracts as well, but the effect is rather lost for the pairs of spot with the front and with the third contracts as the number of lags in the non-linear test increases. However regarding the spot and the sixth futures contract, the spot predictive power is more consistent and it can be argued that there is bidirectional non-linear causality for this pair.

Table 8(a). Results of the bivariate VEC models for silver (see next page for further description).

Table 8(a) Silver (pairwise)

Model/Dependent Variables		c	ECT $_{t-1}$[1] (coint. eq.)	DlogSpot$_{t-1}$	DlogSpot$_{t-2}$	DlogSpot$_{t-3}$	DlogSpot$_{t-4}$	DlogSpot$_{t-5}$	DlogSpot$_{t-6}$
VECM	DlogSpot	-0.000007	-0.836347***	-0.232195***	-0.203881***	-0.187891***	-0.150737***	-0.162109***	-0.117039***
	DlogFut1	-0.000015	-0.082109	0.036414	-0.031807	-0.032485	-0.006363	-0.046959	-0.021558
VECM	DlogSpot	-0.000011	-0.630635***	-0.411031***	-0.355777***	-0.312936***	-0.247868***	-0.235946***	-0.169363***
	DlogFut3	-0.000010	0.007690	-0.042026	-0.100488	-0.091796	-0.053815	-0.083939	-0.047008
VECM	DlogSpot	-0.000024	-0.235011***	-0.763849***	-0.659574***	-0.570301***	-0.457268***	-0.397064***	-0.282259***
	DlogFut6	-0.000008	0.067656	-0.094215	-0.143107**	-0.125193*	-0.080212	-0.103894*	-0.060727

Silver (pairwise) cont.

Model/Dependent Variables		DlogSpot$_{t-7}$	DlogSpot$_{t-8}$	DlogFut$_{t-1}$	DlogFut$_{t-2}$	DlogFut$_{t-3}$	DlogFut$_{t-4}$	DlogFut$_{t-5}$	DlogFut$_{t-6}$
VECM	DlogSpot	-0.017214	-0.005797	0.210625***	0.174379***	0.152488**	0.145012**	0.154500***	0.101730**
	DlogFut1	0.023730	0.012725	-0.097440	-0.014540	0.032508	0.014509	0.021496	0.066393
VECM	DlogSpot	-0.047323	-0.015186	0.404555***	0.339447***	0.291851***	0.255876***	0.241211***	0.165613***
	DlogFut3	0.010280	0.009024	-0.011483	0.059855	0.099363	0.068236	0.065931	0.100342
VECM	DlogSpot	-0.112224***	-0.032620	0.782884	0.670957	0.577343	0.497104	0.434143	0.310758
	DlogFut6	0.002218	0.006925	0.046241	0.107924	0.137307**	0.099918	0.090352	0.118584**

Silver (pairwise) cont.

Model/Dependent Variables		DlogFut$_{t-7}$	DlogFut$_{t-8}$
VECM	DlogSpot	0.083637**	
	DlogFut1	0.029541	
VECM	DlogSpot	0.127040***	0.042127
	DlogFut3	0.049613	-0.029121
VECM	DlogSpot	0.225687	0.091199
	DlogFut6	0.063122	-0.021790

1. For spot-fut1 pair: ECT=logspot-0.998860logfut1-0.004010
For spot-fut3 pair: ECT=logspot-1.004682logfut3+0.017848
For spot-fut6 pair: ECT=logspot-1.017413logfut6-0.063351

*Table 8(a) (see previous page) and Table 8(b). The coefficient results of the VAR/VEC models for silver. Table 8(a) (previous page) shows the results of the bivariate models (pairwise) and table 8(b) shows the results of the multivariate (4x4) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 8(b) Silver (4x4)

Model/Dependent Variables		c	$ECT1_{t-1}$[1] (coint. eq.1)	$ECT2_{t-1}$[1] (coint. eq.2)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$
VECM	DlogSpot	-0.000020	-0.947866***	0.864244***	-0.125407**	-0.101014**	-0.082415*	-0.048140	-0.060110***
	DlogFut1	-0.000012	-0.130182	0.107720	0.082729	0.024516	0.025253	0.049447	0.011576
	DlogFut3	-0.000009	-0.132961	0.148584	0.085626	0.025255	0.024414	0.050132	0.012827
	DlogFut6	-0.000003	-0.134991	0.128742	0.087047	0.026381	0.026350	0.051136	0.012671

Silver (4x4) *cont.*

Model/Dependent Variables	$DlogFut1_{t-1}$	$DlogFut1_{t-2}$	$DlogFut1_{t-3}$	$DlogFut1_{t-4}$	$DlogFut1_{t-5}$	$DlogFut3_{t-1}$	$DlogFut3_{t-2}$	$DlogFut3_{t-3}$
DlogSpot	-0.523025	0.002533	-0.128456	-0.119854	0.185911	0.079623	-0.159680	-0.088063
DlogFut1	-0.952335	0.101956	0.076562	0.170691	-0.399783	0.442890	0.296352	0.481673
DlogFut3	-0.651757	0.219397	0.150492	0.204892	-0.371715	-0.042496	0.046052	0.356910
DlogFut6	-0.768583	0.126006	0.107579	0.208282	-0.367740	0.396251	0.243492	0.456665

Silver (4x4) *cont.*

Model/Dependent Variables	$DlogFut3_{t-4}$	$DlogFut3_{t-5}$	$DlogFut6_{t-1}$	$DlogFut6_{t-2}$	$DlogFut6_{t-3}$	$DlogFut6_{t-4}$	$DlogFut6_{t-5}$
DlogSpot	-0.296143	-0.009479	0.548712	0.224956	0.264845	0.456112	-0.126295
DlogFut1	0.401644	0.531189	0.367072	-0.467218	-0.584013	-0.618616	-0.166644
DlogFut3	0.320369	0.482649	0.549420	-0.335286	-0.531145	-0.571226	-0.147085
DlogFut6	0.399312	0.516371	0.226113	-0.440727	-0.590721	-0.655398	-0.185271

[1.] *ECT1=logspot-1.249384logfut3+0.247595logfut6+0.007385*

ECT2=logfut1-1.442945logfut3+0.442231logfut6+0.003364

*Table 8(c). Causality results for silver. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 8(c) Causality results for Silver

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.5680	0.0802*	0.9775	0.9594	2	0.00896***	0.00000***
					3	0.02647**	0.00003***
					4	0.08805*	0.00134***
					5	0.07112*	0.00156***
					6	0.22760	0.00524***
Spot-Futures 3	0.5250	0.0000***	0.9584	0.9300	2	0.00688***	0.00000***
					3	0.02521**	0.00001***
					4	0.09433*	0.00044***
					5	0.06994*	0.00134***
					6	0.20736	0.00182***
Spot-Futures 6	0.3658	0.0000***	0.9094	0.7982	2	0.00219***	0.00000***
					3	0.00854***	0.00001***
					4	0.03650**	0.00037***
					5	0.04558**	0.00213***
					6	0.11415	0.00292***
Multivariate (4x4)							
Spot-Futures 1	0.5772	0.8703	0.9231	0.9898			
Spot-Futures 3	0.5415	0.9852	0.9695	0.9917			
Spot-Futures 6	0.5320	0.8666	0.9968	0.9945			
Spot-Fut1,3,6	-	0.8835	-	0.9992			

DAX30. Table 9(a) shows the results for the two pairs for DAX30. The coefficients of ECT are significant in the spot equations, but they are also positive. Taking into consideration the form of the co-integrating equations (see table 9(a)), both pairwise models imply that when the spot price is higher than the indicated by the equilibrium value, the spot return increases and in turn escalates the existing deviation. The problem could be answered by the coefficients of the futures equations which are larger in absolute values than those of the spot equations (|0.812962|>|0.502544| and |0.451609|>|0.352707|), but they are not statistically significant. Spot equations in both pairs appear to be affected by several lags of futures and spot returns, while futures equations are not affected by previous spot and futures returns separately. In the multivariate 3x3 VEC model (table 9(b)), futures react to departures from the equilibrium, while spot remains inactive. Also, the influence of separate previous return values seems to have been eliminated for spot equation.

Moving on to the short-run causal effects presented in table 9(c), almost no linear causality was found in pairwise models, with the exception of some evidence of the earliest futures contract leading the spot market. The multivariate 3x3 model also discovered no causal effects. The VECM filtered residuals indicated that no linear dynamics remained hidden from the first step. On the other hand, there is strong evidence at 1% significance level of very consistent bi-directional non-linear causal effects between the spot and the futures of one and two months, as discovered by the non-linear test.

*Table 9(a) and Table 9(b) (see next page). The coefficient results of the VAR/VEC models for DAX30. Table 9(a) shows the results of the bivariate models (pairwise) and table 9(b) (next page) shows the results of the multivariate (3x3) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 9(a) DAX30 (pairwise)

Model/Dependent Variables		c	ECT_{t-1}[1] (coint. eq.)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$	$DlogSpot_{t-6}$
VECM	DlogSpot	0.000348	0.502544**	-0.624340**	-0.724633***	-0.572772**	-0.389417	-0.391254*	-0.370047**
	DlogFut1	0.000342	0.812962	-0.098964	-0.302392	-0.233337	-0.167516	-0.227942	-0.303653
VECM	DlogSpot	0.000347	0.352707**	-0.462295**	-0.488398**	-0.298954	-0.124173	-0.025632	-
	DlogFut2	0.000339	0.451609	0.215137	0.035025	0.102269	0.122903	0.128614	-

DAX30 (pairwise) cont.

Model/Dependent Variables		$DlogFut_{t-1}$	$DlogFut_{t-2}$	$DlogFut_{t-3}$	$DlogFut_{t-4}$	$DlogFut_{t-5}$	$DlogFut_{t-6}$
VECM	DlogSpot	0.656452**	0.699787***	0.572051**	0.326644	0.340755	0.381517**
	DlogFut1	0.131510	0.278349	0.235364	0.107294	0.179255	0.319849
VECM	DlogSpot	0.493221**	0.460772*	0.298502	0.062414	-0.026210	-
	DlogFut2	-0.182052	-0.060571	-0.099541	-0.180222	-0.177705	-

[1.] *For spot-fut1 pair: ECT=logspot-1.001238logfut1+0.011699*

For spot-fut2 pair: ECT=logspot-1.004234logfut2+0.040618

Table 9(b). Results of the multivariate (3x3) VEC model for DAX30 (see previous page for further description).

Table 9(b) DAX30 (3x3)

Model/Dependent Variables		c	ECT1 $_{t-1}$[1] (coint. eq.1)	ECT2 $_{t-1}$[1] (coint. eq.2)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$
VECM	DlogSpot	0.000346	0.356589	0.001695	-0.472063*	-0.505070*	-0.320570	-0.138189	-0.035827
	DlogFut1	0.000342	0.695808***	-0.413500	0.031938	-0.099508	0.002774	0.045707	0.083716
	DlogFut2	0.000339	0.616530**	-0.269434	0.072672	-0.087209	0.001718	0.057028	0.091619

DAX30 (3x3) *cont.*

Model/Dependent Variables	$DlogFut1_{t-1}$	$DlogFut1_{t-2}$	$DlogFut1_{t-3}$	$DlogFut1_{t-4}$	$DlogFut1_{t-5}$	$DlogFut2_{t-1}$	$DlogFut2_{t-2}$	$DlogFut2_{t-3}$
DlogSpot	0.114172	0.342251	0.190704	-0.140530	0.134897	0.389353	0.136102	0.129470
DlogFut1	-0.267756	0.084139	0.052029	-0.229092	0.099069	0.267507	-0.010734	-0.052457
DlogFut2	0.328746	0.498367	0.324736	-0.066610	0.172818	-0.368422	-0.436449	-0.324263

DAX30 (3x3) *cont.*

Model/Dependent Variables	$DlogFut2_{t-4}$	$DlogFut2_{t-5}$
DlogSpot	0.216348	-0.150609
DlogFut1	0.123654	-0.232124
DlogFut2	-0.048897	-0.313825

[1.] *ECT1=logspot-1.004518logfut2+0.042394*
ECT2=logfut1-1.003243logfut2+0.030351

*Table 9(c). Causality results for DAX30. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 9(c) Causality results for DAX30

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.5238	0.0890*	0.9933	0.9915	2	0.00006***	0.00106***
					3	0.00005***	0.00037***
					4	0.00010***	0.00055***
					5	0.00026***	0.00094***
					6	0.00036***	0.00119***
Spot-Futures 2	0.8306	0.2708	0.80999	0.7611	2	0.00000***	0.00061***
					3	0.00001***	0.00035***
					4	0.00018***	0.00058***
					5	0.00053***	0.00078***
					6	0.00037***	0.00064***
Multivariate (3x3)							
Spot-Futures 1	0.9625	0.8512	0.8408	0.9893			
Spot-Futures 2	0.9405	0.8552	0.8348	0.9120			
Spot-Fut1,2	-	0.7478	-	0.9704			

CAC40. Table 10(a) presents the results of the bivariate models for CAC40. As in most of previous cases, the spot market corrects any deviations from the equilibrium for the pair of spot and earliest futures contract. No co-integration was found for the pair of spot and two-month contract. Spot and futures current returns of CAC40 are shown to follow a different pattern than those of previous assets regarding lag coefficients. Particularly, spot equation in the first pair does not appear to be influenced by past values of spot and futures returns independently, but it is affected by the second lag of futures returns in the second pair. On the other hand, futures equation in both pairs are more heavily affected by past returns of both markets. When the multivariate 3x3 model is examined (table 10(b)) it is again the spot market that tries to erase deviation errors in the equilibrium relationship. Spot equation continues to neglect any (auto)-regressive nature, while futures equations are directed by spot and two-month futures returns of previous day.

The short-run causal effects are shown in table 10(c). Linear investigation with VECMs indicated no Granger causality between spot and the earliest futures, but it detected strong dominance of spot on the two-month futures contract. When all variables were tested in the multivariate 3x3 model, spot dominance spread to the one-month futures as well. For both bivariate and multivariate models, VECM filtered residuals presented no further Granger causality. The test for non-linear dynamics showed that there is a feedback mechanism for both pairs examined, considering the 5% significance level. However, it appears that the causal channels from futures to spot are more significant with lower p-values through all embedding dimensions than the respective channels from spot to futures.

Table 10(a). Results of the bivariate VEC models for CAC40 (see table below for further description).

Table 10(a) CAC40 (pairwise)

Model/Dependent Variables		c	ECT_{t-1}[1] (coint. eq.)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogFut_{t-1}$	$DlogFut_{t-2}$
VECM	DlogSpot	0.000146	-0.037036***	-0.018016	-	0.027983	-
	DlogFut1	0.000165	-0.017859	0.108840	-	-0.098381	-
VAR	DlogSpot	0.000154	-	0.025568	0.137593	-0.016560	-0.168770**
	DlogFut2	0.000169	-	0.345874***	0.252968***	-0.325007***	-0.272762***

[1.] *For spot-fut1 pair: ECT=logspot-0.881178logfut1-1.012731*

*Table 10(a) and Table 10(b). The coefficient results of the VAR/VEC models for CAC40. Table 10(a) shows the results of the bivariate models (pairwise) and table 10(b) shows the results of the multivariate (3x3) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 10(b) CAC40 (3x3)

Model/Dependent Variables		c	$ECT1_{t-1}$[1] (coint. eq.1)	$ECT2_{t-1}$[1] (coint. eq.2)	$DlogSpot_{t-1}$	$DlogFut1_{t-1}$	$DlogFut2_{t-1}$
VECM	DlogSpot	0.000146	-0.041055***	0.010759	-0.012223	0.042535	-0.020153
	DlogFut1	0.000166	-0.028879	-0.055372	0.195695**	0.023537	-0.207415*
	DlogFut2	0.000162	-0.031034*	0.029607	0.285382***	-0.018334	-0.245862**

[1.] *ECT1=logspot-0.883519logfut3-0.993856*

ECT2=logfut1-1.008009logfut2+0.066118

*Table 10(c). Causality results for CAC40. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 10(c) Causality results for CAC40

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.1775	0.7034	0.8249	0.8903	2	0.12141	0.00021***
					3	0.04513**	0.00003***
					4	0.02594**	0.00016***
					5	0.02392**	0.00038***
					6	0.01332**	0.00233***
Spot-Futures 2	0.0003***	0.1491	0.9891	0.9492	2	0.02404**	0.00004***
					3	0.00481***	0.00004***
					4	0.01796**	0.00166***
					5	0.01917**	0.00399***
					6	0.05621*	0.05073*
Multivariate (3x3)							
Spot-Futures 1	0.0437**	0.6495	0.4971	0.9424			
Spot-Futures 2	0.0031***	0.8518	0.4160	0.7190			
Spot-Fut1,2	-	0.8957	-	0.8783			

SP500. The results of the pairwise models for SP500 are shown in table 11(a). The coefficients of ECT for the two first pairs indicate that correction in the long-term equilibrium is done by the futures market. The third pair indicates that neither the spot nor the futures contract complies with their long-run relationship. Past spot and futures returns are generally significant for spot current returns, while this not the case for futures current returns. Also, constants are significant for all models indicating that the average SP500 spot and futures returns are non-zero. Absence of correction by both the spot and the corresponding futures is hinted by the multivariate 4x4 model as well (table 11(b)), as all coefficients are statistically zero even at 10% significance level. Lag coefficients indicate that spot current return is not so boldly explained by futures past returns as it did in pairwise models, while futures current return present evidence of auto-regressive nature.

Table 11(c) presents the results of causality tests. In pairwise modelling, strong linear causal effects were detected from the second and third to expire futures contracts to the spot market. However, in the multivariate 4x4 model those causal dynamics move to the first and second contracts, albeit somewhat weaker in strength. There is also clear joint dominance of futures over spot. The tests on the VECM filtered residuals discovered no further linear causality as anticipated. The Diks and Panchenko (2006) test revealed strong and consistent through all lags non-linear feedback relationship between spot and futures contracts of all maturities. With the exception of the pair of spot and front contract, the feedback effect is somewhat weakened in higher number of lags at the expense of futures dominance over spot.

*Table 11(a) and Table 11(b) (see next page). The coefficient results of the VAR/VEC models for SP500. Table 11(a) shows the results of the bivariate models (pairwise) and table 11(b) (next page) shows the results of the multivariate (4x4) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 11(a) SP500 (pairwise)

Model/Dependent Variables		c	ECT_{t-1}[1] (coint. eq.)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$	$DlogFut_{t-1}$
VECM	DlogSpot	0.000435**	0.012131	-0.373492**	-0.304359**	-0.315661**	-0.222646*	-	0.324262**
	DlogFut1	0.000437**	0.269179**	0.062483	-0.033783	-0.161859	-0.169795	-	-0.109055
VECM	DlogSpot	0.000469***	0.051946	-0.622829***	-0.371526**	-0.393345**	-0.237939	-0.167460	0.569575***
	DlogFut2	0.000472***	0.138301*	-0.036392	0.006790	-0.161284	-0.105439	-0.100754	-0.008229
VECM	DlogSpot	0.000470**	0.043832	-0.611860***	-0.366564**	-0.377980**	-0.222250 -	-0.157086	0.556240***
	DlogFut3	0.000474**	0.083262	0.018775	0.048596	-0.117630	0.070129	-0.079980	-0.062363

SP500 (pairwise) cont.

Model/Dependent Variables		$DlogFut_{t-2}$	$DlogFut_{t-3}$	$DlogFut_{t-4}$	$DlogFut_{t-5}$
VECM	DlogSpot	0.304079**	0.283250**	0.211342*	-
	DlogFut1	0.032322	0.135055	0.150827	-
VECM	DlogSpot	0.363646**	0.358493**	0.219678	0.093034
	DlogFut2	-0.012000	0.132952	0.082927	0.023321
VECM	DlogSpot	0.356919**	0.341164**	0.202674	0.081492
	DlogFut3	-0.052554	0.089211	0.047850	0.001985

[1.] *For spot-fut1 pair: ECT=logspot-0.997116logfut1-0.023374*

For spot-fut2 pair: ECT=logspot-0.991050logfut2-0.071716

For spot-fut3 pair: ECT=logspot-0.984725logfut2-0.121799

Table 11(b). Results of the multivariate (4x4) VEC model for SP500 (see previous page for further description).

Table 11(b) SP500 (4x4)

Model/Dependent Variables		c	ECT1 $_{t-1}$[1] (coint. eq.1)	ECT2 $_{t-1}$[1] (coint. eq.2)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogFut1_{t-1}$
VECM	DlogSpot	0.000433**	-0.092635	0.294822	-0.466760***	-0.324947*	-0.295408*	-0.149607	-0.637287*
	DlogFut1	0.000435**	0.216794	-0.421225	-0.093007	-0.115363	-0.182575	-0.112030	-0.917399**
	DlogFut2	0.000432**	0.191692	0.055343	-0.017545	-0.069539	-0.169945	-0.102950	-0.545190
	DlogFut3	0.000433**	0.186491	0.057266	-0.014114	-0.067800	-0.169060	-0.103848	-0.539523

SP500 (4x4) *cont.*

Model/Dependent Variables	$DlogFut1_{t-2}$	$DlogFut1_{t-3}$	$DlogFut1_{t-4}$	$DlogFut2_{t-1}$	$DlogFut2_{t-2}$	$DlogFut2_{t-3}$	$DlogFut2_{t-4}$	$DlogFut3_{t-1}$
DlogSpot	0.017190	-0.017567	0.230987	4.103419*	-1.715752	3.169444	2.444717	-3.038807
DlogFut1	-0.173276	-0.121488	0.194512	4.822220**	-1.233297	3.572891*	2.836068	-3.845443*
DlogFut2	0.109591	0.069704	0.292335	4.580855**	-1.428276	3.184060	2.568687	-4.044618*
DlogFut3	0.116201	0.076227	0.301716	4.690179**	-1.432028	3.255414	2.569515	-4.161939**

SP500 (4x4) *cont.*

Model/Dependent Variables	$DlogFut3_{t-2}$	$DlogFut3_{t-3}$	$DlogFut3_{t-4}$
DlogSpot	2.011111	-2.876595	-2.525751
DlogFut1	1.510237	-3.281446	-2.923650
DlogFut2	1.382153	-3.094982	-2.759705
DlogFut3	1.378320	-3.173244	-2.768508

[1.] *ECT1=logspot-2.484725logfut2+1.484299logfut3+0.002589*

ECT2=logfut1-1.964714logfut2+0.964716logfut3-0.000278

*Table 11(c). Causality results for SP500. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 11(c) Causality results for SP500

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.5171	0.1752	0.9748	0.9719	2	0.00072***	0.00000***
					3	0.00038***	0.00000***
					4	0.00027***	0.00000***
					5	0.00098***	0.00000***
					6	0.00643***	0.00001***
Spot-Futures 2	0.8201	0.0020***	0.9373	0.9717	2	0.00465***	0.00000***
					3	0.00577***	0.00000***
					4	0.00157***	0.00000***
					5	0.01547**	0.00000***
					6	0.04586**	0.00001***
Spot-Futures 3	0.8799	0.0011***	0.9223	0.9664	2	0.00384***	0.00000***
					3	0.00629***	0.00000***
					4	0.00190***	0.00000***
					5	0.02548**	0.00000***
					6	0.07492*	0.00001***
Multivariate (4x4)							
Spot-Futures 1	0.8474	0.0357**	0.9517	0.7386			
Spot-Futures 2	0.8480	0.0783*	0.9354	0.8037			
Spot-Futures 3	0.8481	0.1357	0.9355	0.7762			
Spot-Fut1,2,3	-	0.0082***	-	0.9770			

Nasdaq100. Table 12(a) presents the results of the bivariate VEC models for Nasdaq100. The coefficients of ECT indicate that the long-run relationship between the spot and the futures contracts is fragile and not corrected by spot or futures movements in pairwise models, but it is secured in the 3x3 multivariate model through futures movements (table 12(b)). Furthermore, regarding pairwise models and lag coefficients, spot equation seems to have some autoregressive components for the first pair, while it seems to be influenced both by its past values and past futures return values in the second pair. Equations of both futures contracts indicate that futures returns are affected by some late lags of spot and futures returns. It is also noticeable that, as in the case of SP500, constants are significant in all models.

Linear Granger causality approached with VEC modelling concluded mixed results as shown in the table 12(c). The earliest futures leads the spot, but there is a feedback mechanism for the spot and the second to expire futures. On the other hand, in the multivariate 3x3 model, there is slight evidence that the spot leads the earliest futures contract, while the bi-directional causality between the spot and the second to expire futures remains, albeit the causal transmission from spot to futures weakens relatively to the corresponding pairwise model. Again, the VEC models seems to have captured the linear effects entirely, as the tests on their residuals detected no further linear effects. In the non-linear context, very strong and consistent bi-directional causal dynamics were found for the spot and the futures contracts of both maturities.

It is noted that tests on residuals, to assure entire capture of linear causality in the previous step, were done with VAR models as no co-integration was found and with one lag chosen. This applies to all assets.

In table 13, co-integration and Granger causality results are summarized for all assets.

*Table 12(a) and Table 12(b) (see next page). The coefficient results of the VAR/VEC models for Nasdaq100. Table 12(a) shows the results of the bivariate models (pairwise) and table 12(b) (next page) shows the results of the multivariate (3x3) model. The first two columns present the chosen model (VAR or VECM) and the dependent variables of the model. The rest of the columns present the coefficients of the independent variables participating in the corresponding model. *, ** and *** indicate statistical importance of the coefficients at 10%, 5% and 1% significance level respectively. All variables are in their log form and D denotes the first difference operation. The number of lags for each model was chosen with the Schwarz information criterion (SIC).*

Table 12(a) Nasdaq100 (pairwise)

Model/Dependent Variables		c	ECT_{t-1}[1] (coint. eq.)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$	$DlogSpot_{t-6}$
VECM	DlogSpot	0.000692***	-0.127407	-0.328128*	-0.278998	-0.385057**	-0.181569	0.108118	0.041948
	DlogFut1	0.000685***	0.238236	0.140097	0.084197	-0.098654	0.015501	0.254697	0.188921
VECM	DlogSpot	0.000674***	0.013507	-0.620488***	-0.374760**	-0.487272***	-0.137631	0.101545	-0.005294
	DlogFut2	0.000667***	0.131154	0.061190	0.204775	-0.102986	0.100294	0.258366*	0.081400

Nasdaq100 (pairwise) *cont.*

Model/Dependent Variables		$DlogSpot_{t-7}$	$DlogSpot_{t-8}$	$DlogFut_{t-1}$	$DlogFut_{t-2}$	$DlogFut_{t-3}$	$DlogFut_{t-4}$	$DlogFut_{t-5}$	$DlogFut_{t-6}$
VECM	DlogSpot	0.183846	0.105239	0.305764	0.265169	0.349322*	0.172052	-0.155696	-0.047051
	DlogFut1	0.294206**	0.159939	-0.158448	-0.095719	0.069202	-0.027424	-0.304011*	-0.193878
VECM	DlogSpot	-	-	0.600521***	0.355100**	0.451479***	0.126347	-0.150534	-0.000244
	DlogFut2	-	-	-0.072324	-0.217063	0.072054	-0.107673	-0.306699**	-0.091730

Nasdaq100 (pairwise) *cont.*

Model/Dependent Variables		$DlogFut_{t-7}$	$DlogFut_{t-8}$
VECM	DlogSpot	-0.189867	-0.143113
	DlogFut1	-0.298635**	-0.194090*
VECM	DlogSpot	-	-
	DlogFut2	-	-

[1.] *For spot-fut1 pair: ECT=logspot-0.997839logfut1-0.018313*

For spot-fut2 pair: ECT=logspot-0.993880logfut2-0.051507

Table 12(b). Results of the multivariate (3x3) VEC model for Nasdaq100 (see previous page for further description).

Table 12(b) Nasdaq100 (3x3)

Model/Dependent Variables		c	ECT1 $_{t-1}$[1] (coint. eq.1)	ECT2 $_{t-1}$[1] (coint. eq.2)	$DlogSpot_{t-1}$	$DlogSpot_{t-2}$	$DlogSpot_{t-3}$	$DlogSpot_{t-4}$	$DlogSpot_{t-5}$
	DlogSpot	0.000669***	-0.123851	0.252485	-0.509038***	-0.328039*	-0.460512**	-0.157784	0.102671
VECM	DlogFut1	0.000664***	0.420270**	-0.574011*	-0.222550	-0.110512	-0.312956*	-0.090005	0.118145
	DlogFut2	0.000661***	0.224901	-0.173156	-0.029253	0.060212	-0.224282	-0.028077	0.168000

Nasdaq100 (3x3) *cont.*

Model/Dependent Variables	$DlogSpot_{t-6}$	$DlogFut1_{t-1}$	$DlogFut1_{t-2}$	$DlogFut1_{t-3}$	$DlogFut1_{t-4}$	$DlogFut1_{t-5}$	$DlogFut1_{t-6}$	$DlogFut2_{t-1}$
DlogSpot	-0.031488	-0.107534	0.192430	0.287361	0.438419*	0.204066	0.206739	0.596647***
DlogFut1	-0.004497	-0.209110	0.193635	0.301653	0.476739*	0.240173	0.201436	0.417453*
DlogFut2	0.013583	0.303118	0.640284**	0.645095**	0.669999***	0.401939*	0.275599*	-0.284726

Nasdaq100 (3x3) *cont.*

Model/Dependent Variables	$DlogFut2_{t-2}$	$DlogFut2_{t-3}$	$DlogFut2_{t-4}$	$DlogFut2_{t-5}$	$DlogFut2_{t-6}$
DlogSpot	0.117158	0.140241	-0.288882	-0.355146*	-0.177409
DlogFut1	-0.099001	-0.015280	-0.397264	-0.408844*	-0.198980
DlogFut2	-0.710079***	-0.448160*	-0.645329***	-0.616796***	-0.295851*

[1.] *ECT1=logspot-0.993807logfut2-0.052104*

ECT2=logfut1-0.996024logfut2-0.033339

*Table 12(c). Causality results for Nasdaq100. The first column presents the variables investigated for Granger causality. The second and the third columns present the p-values for the raw data (log-time series) based on the appropriate VAR/VEC model for each case (linear causal effects), while the fourth and the fifth columns show the p-values for the residuals of those VAR/VEC models (linear causal effects). The null hypothesis of S→F is that the spot does not Granger cause the corresponding futures (the equivalent applies for F→S). *, ** and *** indicate rejection of the null at 10%, 5% and 1% significance level respectively. The last three columns present the embedding dimensions and the p-values for the Diks and Panchenko (2006) test conducted on the VAR/VECM filtered residuals (non-linear causal effects).*

Table 12(c) Causality results for Nasdaq100

Variables	Linear Granger causality				Non-linear Granger causality		
	Raw data		VAR/VECM filtered residuals		VAR/VECM filtered residuals		
Pairwise (2x2)	S→F	F→S	S→F	F→S	Embed. dimension	S→F	F→S
Spot-Futures 1	0.1157	0.0238**	0.9953	0.9931	2	0.00003***	0.00000***
					3	0.00144***	0.00000***
					4	0.00086***	0.00000***
					5	0.00056***	0.00001***
					6	0.00302***	0.00026***
Spot-Futures 2	0.0113**	0.0000***	0.9760	0.9927	2	0.00001***	0.00000***
					3	0.00025***	0.00000***
					4	0.00129***	0.00000***
					5	0.00049***	0.00002***
					6	0.00359***	0.00032***
Multivariate (3x3)							
Spot-Futures 1	0.0864*	0.2347	0.9651	0.8904			
Spot-Futures 2	0.0605*	0.0025***	0.9810	0.8635			
Spot-Fut1,2	-	0.0002***	-	0.9852			

Table 13. Aggregate results of co-integration and Granger causality for all assets. S→F denotes causality from spot to futures and F→S denotes causality from futures to spot. Y and N denote presence and absence of co-integration/causality respectively, at 5% significance level. For non-linear causality, Y additionally requires consistent presence of causality for at least 4 of the 5 lags considered in the non-linear test (see tables 5-12(c)).

Table 13 Aggregate co-integration and Granger causality results

			Linear Granger causality		Non-linear Granger causality	
		Co-integration	S→F	F→S	S→F	F→S
WTI oil	Spot-Fut1	Y	Y	N	Y	Y
	Spot-Fut2	Y	Y	Y	N	Y
	Spot-Fut3	Y	Y	Y	N	Y
	Spot-Fut6	N	Y	N	N	Y
Natural gas	Spot-Fut1	Y	Y	Y	Y	Y
	Spot-Fut2	Y	N	Y	N	Y
	Spot-Fut3	Y	N	Y	N	Y
	Spot-Fut6	Y	N	Y	N	Y
Gold	Spot-Fut1	Y	N	Y	N	N
	Spot-Fut2	Y	N	Y	N	Y
	Spot-Fut3	Y	N	Y	N	Y
	Spot-Fut6	Y	N	Y	N	Y
Silver	Spot-Fut1	Y	N	N	N	Y
	Spot-Fut3	Y	N	Y	N	Y
	Spot-Fut6	Y	N	Y	Y	Y
DAX30	Spot-Fut1	Y	N	N	Y	Y
	Spot-Fut2	Y	N	N	Y	Y
CAC40	Spot-Fut1	Y	N	N	Y	Y
	Spot-Fut2	N	Y	N	Y	Y
SP500	Spot-Fut1	Y	N	N	Y	Y
	Spot-Fut2	Y	N	Y	Y	Y
	Spot-Fut3	Y	N	Y	Y	Y
Nasdaq100	Spot-Fut1	Y	N	Y	Y	Y
	Spot-Fut2	Y	N	Y	Y	Y

2.4 Discussion

This section is also classified by product for better evaluation of results and comparison with previous studies. A general conclusion is given in the end considering all assets.

WTI oil. In a rather expected continuation of the literature, the investigation of WTI oil in this work captured mixed results. Spot price and futures of one, two, three and six-month to maturity were used for examination. Regarding long-run equilibrium, it appears that oil markets are co-integrated considering the one, two and three-months to maturity futures, while the six-month futures contract was founded not to be co-integrated with the spot price (table 13). Investors interested in the six month hedging period should opt for shorter contracts in a rolling basis instead of the standard six-month contract.

Regarding short-run dynamics, the oil markets seem not to be efficient. Overall results (table 13), which indicate Granger causality to be unidirectional from spot to futures or bidirectional in the linear context and mostly unidirectional from futures to spot in the non-linear context, appear to be in disagreement with the study of Silvapulle and Moosa (1999) and in liaison with the study of Bekiros and Diks (2008). In particular, the former study revealed futures dominance and bidirectional causal effects in the linear and non-linear context respectively, while the latter study found the same causal effects, but in the opposite contexts. Also, considering that the study of Bekiros and Diks (2008) expands from 1991 to 2007 while this work refers to the sample from 2010 to 2019 it could be argued that WTI oil spot and futures markets behave in about the same way, linearly and non-linearly, in the last three decades and roughly excluding the recent crisis years. It can be concluded that both markets have predictive power over each other and that price discovery process happens both in the spot and futures markets accompanied by dynamic dispute regarding the retention of the leading role.

Natural gas. Results for natural gas illustrated a somewhat more consistent picture than results for WTI oil did. Spot price and one, two, three and six-month to maturity futures were used. All pairs were found to be co-integrated (table 13) with futures driving spot price in the long-run (see ECTs in table 6(a)).

The short-run dynamics showed a feedback mechanism between the spot and the front month futures and unidirectional Granger causality from futures to spot for longer maturities under both linear and non-linear examination (table 13). The results roughly agree with the study of Zhang and Liu (2018) regarding linear investigation with the exception of the front month contract. However, there is contradiction regarding the non-linear approach, as Zhang and Liu (2018) found bidirectional causality for all maturities using the Diks and Panchenko (2006) test. Also, the results concerning the front month futures are in conflict with the study of Dergiades et al. (2018) who detected futures dominance for the one-month contract both in time and frequency domains.

Gold. The general picture of gold markets illustrates rather undeniably the dominant position of futures over spot both in linear and non-linear contexts. Gold spot price was examined alongside the first, second, third and sixth listed for delivery futures contracts. Co-integration exists for all pairs (table 13) and coefficients of ECTs (table 7(a)) showed that futures lead the spot price in the long-run.

Regarding short-run dynamics, the linear tests revealed the leading role of futures of all maturities (table 13). Non-linear tests also revealed that futures lead the spot market with the exception of the front contract. The results are consonant with previous studies of Joseph et al. (2014), Jena et al. (2018) and Torun et al. (2020), but not with that of Cagli et al. (2020) who found a clear feedback relationship.

Silver. Spot price and the first, third and sixth listed for delivery futures contracts were used for silver. Again in the long-run, co-integration exists between spot and futures (table 13), with futures of all maturities leading the spot which corrects any deviation from the equilibrium (see ECTs in table 8(a)).

Linear short-run dynamics of pairwise VECMs revealed unidirectional Granger causality from futures to spot with the exception of the front contract (table 13). Additionally, non-linear approach also detected strong unidirectional Granger causality from futures to spot considering the front and third contracts, but it detected a feedback mechanism between the spot and sixth contract. Overall, the results are roughly in agreement with the study of Torun et al. (2020) who found that futures drive the spot for all frequencies of their wavelet analysis and with the study of Jena et al. (2019) who used causality-in-quantile to reach a similar conclusion. There is also agreement with the VECM analysis of the study of Joseph et al. (2014) but disagreement with the frequency domain analysis of the same study. Furthermore, there are contradictions with Cagli et al. (2020) who found bidirectional causality under the Diks and Panchenko (2006) approach.

DAX30. The German DAX30 was examined considering the spot value and the first and second listed for delivery futures contracts. A long-run equilibrium relationship exists for both pairs (table 13), however spot prices appear to aggravate deviations (see ECTs in table 9(a)).

Regarding linear short-run dynamics, no causality was detected for the two pairs under investigation (table 13). Non-linear testing detected strong and consistent bidirectional causality between spot and futures of both maturities. The results are in contradiction with the study of Li (2008) who found a feedback linear relationship using both VECM and MS-VECM methods and with the study of Torun et al. (2020) who found evidence of futures dominance in high frequencies using wavelet analysis.

CAC40. The French CAC40 was investigated considering the spot value and the one and two-month futures contracts. Co-integration exists for the pair of spot and front month futures (table 13) with the latter leading the former (see ECTs in table 10(a)), but no equilibrium relationship was found for the second pair.

Concerning linear short-run dynamics, pairwise VECMs discovered unidirectional causal effects from spot to the second month futures (table 13). Non-linear testing detected consistent bidirectional Granger causality for both pairs. The results disagree with the study of Torun et al. (2020) who did not find any causal dynamics for CAC40.

SP500. The US SP500 was studied using its spot value and the first three futures contracts listed for delivery. For all pairs, equilibrium relationships exist in the presence of co-integration (table 13), with futures reacting to deviations only for the two first pairs (see ECTs in table 11(a)).

Regarding short-run dynamics, linear testing detected strong Granger causality from the second and third futures to spot (table 13). Moving on to non-linear testing, bidirectional causality was revealed for all pairs. The results disagree with previous studies of Li (2008) and Chen and Zheng, (2008) who spotted futures dominance over spot as well as that of Torun et al. (2020) who found spot dominance over futures, all of them considering front month futures contracts only.

Nasdaq100. Spot and the first two tradable futures contracts were used for investigation of Nasdaq100. Co-integration exists for both pairs (table 13), but as it partially happened in the case of SP500, neither spot nor futures tries to correct any discrepancies of their long-run relationship (see ECTs in table 12(a)).

Regarding short-run dynamics, pairwise VECMs detected evidence that futures of both maturities Granger cause spot market (table 13). The Diks and Panchenko (2006) method revealed a feedback mechanism between spot and futures of both maturities.

The big picture of the analysis of the relationship of spot and futures markets for the commodities and indices under consideration can be summarized as follows:

- Firstly, futures markets appear to fulfill their risk management role which is crucial for their very survival according to Garbade and Silver (1983) and Brorsen and Fofana (2001). The long-run equilibrium relationship in the presence of co-integration which qualifies futures markets as adequate hedging tools (Ankamah-Yeboah et al., 2017) and implies pricing efficiency (Chen and Zheng, 2008; Ankamah-Yeboah et al., 2017) is confirmed for all pairs, except for the cases of the six-month WTI oil and two-month CAC40 futures contracts (table 13). According to Silvapulle and Moosa (1999) absence of co-integration indicates market inefficiency and rejection of the cost of carry model should be associated with the non-stationarity of interest rates and the convenience yield included in the model, hence futures of longer maturities are quite likely not to be found co-integrated with the spot market. Besides, for the case of WTI oil, Wang and Wu (2013) argue that futures of longer maturities are preferred by hedgers and oil project stakeholders who will react conservatively to non-major new information.
- Secondly, in the long-run, futures markets lead spot markets regarding commodities as shown by the coefficients of ECTs (tables 5-8(a)), while this leading role is not clear in the case of financial indices (tables 9-12(a)).

Two peculiarities occurred concerning equilibrium deviations. In the case of DAX30, the spot market exaggerates deviations while futures correct them and follow the spot (see ECTs in table 9(a)). According to Bohl et al. (2011), such abnormal exaggerations may happen due to momentum effect. This derives from the fact that the underlying index cannot be directly traded and some stocks participating in DAX30 may continue to raise due to momentum anomaly. Tswei and Lai (2009) advocate that ECT coefficients may have the same sign as a result of over-reaction to news among investors in the less informative market or under-reaction among investors in the more informative market.

Also, in the case of the last bivariate and the multivariate VECMs for SP500 and both bivariate VECMs for Nasdaq100, neither the spot nor the futures comply with the long-run relationships (see ECTs in tables 11(a-b) and 12(a)). This ‘’indifference’’ for equilibrium, when it exists, by both spot and futures could be justified if the basis does not override a certain threshold which would trigger arbitrage trading (Huang et al., 2009).

- Thirdly, as far as short-run causal dynamics are concerned (table 13), the results are mixed in overall. For WTI oil, it seems that there are bidirectional or unidirectional from spot to futures causal channels, but futures appear to dominate the spot in the non-linear context excluding the feedback relationship of the first pair. For the rest of commodities, futures generally lead the spot both linearly and non-linearly with the exception of bidirectional causality for the first pair of natural gas and for the last pair of silver.

  Regarding financial indices, there is evidence that spot linearly leads the second futures contract for CAC40, while futures appear to linearly dominate the spot for the cases of SP500 and Nasdaq100. However, the non-linear method reveals bidirectional lead-lag relationships for all pairs and all indices.

  It is noteworthy that the bivariate linear causal relationships change significantly for almost all assets when futures contracts of different maturities are studied altogether in multivariate models, particularly for commodities (see multivariate parts of tables 5-12(c)). Hence, any pairwise dynamics should be approached with caution in the absence of effects of other variables.

Taking into consideration both linear and non-linear tests and with the exception of gold and partially gas and silver whose futures Granger-cause the respective spot markets in most pairs, it appears that the hypothesis of Kawaller et al. (1987) is confirmed. Neither the spot nor the futures market leads consistently, as a set of new information is not integrated in the markets thoroughly but partially and gradually, for investors, both in the spot and futures markets, filter new information with respect to their positions creating bidirectional lead-lag relationships either linearly or non-linearly. Regarding gold, gas and silver, it can be argued that the futures leading role in informational transmissions and price discovery can be attributed to speculators who prefer to trade in futures markets due to lower transaction costs, availability of short selling, less strict regulations and their indifference for the underlying commodities. For medium six-month or longer maturities contracts, it could be the hedgers who provoke changes in futures markets. However, any conclusion at this point should be approached with reservation for literature provides several arguments for the futures leading role (see sub-section 1.2.3.3.1) and further investigation of the particular markets is needed. Furthermore, Theissen (2012) hypothesis that spot financial indices concede dominion to futures due to infrequent spot trading seems not to be confirmed as shown by the pairs of all indices examined. Also, for all assets, the predictive power of causal channels spotted can be theoretically exploited by investors devising a suitable trading strategy. However, practical obstacles, such as transaction costs, availability of short-selling, liquidity and slippage time have to be overcome if such a strategy is to be realized.

Finally, it is notable that with the Diks and Panchenko (2006) approach, very strong and consistent non-linear causal dynamics were revealed in both directions. According to Abhyankar (1996), non-linear effects can be induced by non-linear transaction costs, the market microstructure and noise traders. Wilson et al. (1996) argued that periods of extreme volatility can add up to non-linearity. Considering that speculation creates volatility and it also includes irrational trading, it can be argued that speculators provoke non-linear causality. Galeotti et al. (2003) underline that price inelasticity and market defragmentation are the main reasons for asymmetric transmissions in the energy sector, while Dergiades et al. (2018) notice the role of weather conditions in non-linear dynamics in the natural gas market. Furthermore, Arouri et al. (2013) mention industry evolutions and economic crises as potential sources of non-linear dynamics for consumption commodities, seemingly due to the shocking innovations those sources are accompanied with.

Conclusion

This work was concerned with the causal dynamics between spot and futures markets, dynamics which can provide insight into the price discovery and market efficiency concepts. The first chapter provided the basics of derivatives, including forwards, futures, options and swaps, and the interrelations between the spot and futures markets from a theoretical perspective with priority given to the lead-lag relationships. Additionally, the relevant to the topic academic literature was reviewed, primarily that of the last decade. In the second chapter, the empirical investigation was conducted. Daily data, from 4 January 2010 to 4 November 2019, for four commodities, that is WTI oil, natural gas, gold and silver and for four financial indices, that is the DAX30, CAC40, SP500 and Nasdaq100 were collected for this purpose. For each asset, futures contracts of various maturities were matched in pairs with the corresponding spot price, as well as altogether in multivariate models. Granger causal effects were tested in two steps. In the first step, linear Granger causality was investigated with the appropriate VAR/VEC models. The filtered residuals were also tested for linear causal effects to ensure that no linear dynamics had remained. In the second step, non-linear Granger causality was investigated with the Diks and Panchenko (2006) test applied to the previously purified residuals.

In accordance with the big picture of literature review, results were mixed, as spot and futures markets appear to behave uniquely for each asset. Long-run equilibrium was confirmed for almost all pairs. Regarding Granger causality and commodities, linear examination revealed that futures lead spot market in almost all pairs of gas, gold and silver, but there is either spot dominance or bidirectional lead in the pairs of WTI oil. The non-linear approach further enhanced the leading role of futures for all commodities, but a few non-linear feedback mechanisms were also revealed.

Regarding financial indices in the linear context, no causality was detected for the DAX30, while evidence was found that spot partially leads futures for the CAC40 and that futures lead spot for the SP500 and Nasdaq100. Under the non-linear approach significant bidirectional causal channels emerged for all pairs and all financial indices, as linear tests underestimated the causal transmissions and predictive power of both spot and futures markets over each other.

References

Abhyankar, A., 1996. Does the stock index futures market tend to lead the cash? New evidence from the FT-SE 100 stock index futures market. In Working Paper No. 96-01, Department of Accounting and Finance University of Stirling.

Agiakloglou, C. and Newbold, P., 1992. Empirical evidence on Dickey‐Fuller‐type tests. Journal of Time Series Analysis, 13(6), pp.471-483.

Agyekum, C.K., Huang, H. and Chen, J., 2017. The impact of the Chinese cornstarch futures on spot market and corn futures market. Cogent Economics & Finance, 5(1), p.1405580.

Alzahrani, M., Masih, M. and Al-Titi, O., 2014. Linear and non-linear Granger causality between oil spot and futures prices: A wavelet based test. Journal of International Money and Finance, 48, pp.175-201.

Anderson, R.W. and Danthine, J.P., 1983. Hedger diversity in futures markets. The Economic Journal, 93(370), pp.370-389.

Ankamah-Yeboah, I., Nielsen, M. and Nielsen, R., 2017. Price formation of the salmon aquaculture futures market. Aquaculture Economics & Management, 21(3), pp.376-399.

ap Gwilym, R., Ebrahim, M.S., El Alaoui, A.O., Rahman, H. and Taamouti, A., 2019. Financial frictions and the futures pricing puzzle. Economic Modelling.

Arfaoui, M., 2018. On the spot-futures relationship in crude-refined petroleum prices: New evidence from an ARDL bounds testing approach. Journal of Commodity Markets, 11, pp.48-58.

Arouri, M.E.H., Jawadi, F. and Nguyen, D.K., 2012. Nonlinearities in carbon spot-futures price relationships during Phase II of the EU ETS. Economic Modelling, 29(3), pp.884-892.

Arouri, M.E.H., Jawadi, F. and Mouak, P., 2013. Testing the efficiency of the aluminium market: evidence from London metal exchange. Applied Financial Economics, 23(6), pp.483-493.

Asche, F., Misund, B. and Oglend, A., 2016. The spot-forward relationship in the Atlantic salmon market. Aquaculture Economics & Management, 20(2), pp.222-234.

Ayadi, O.F., 1994. The efficiency of price discovery in the stock market and macroeconomic variables: An empirical investigation. African Review of Money Finance and Banking, pp.33-55.

Baek, E. and Brock, W., 1992. A general test for nonlinear Granger causality: Bivariate model. Iowa State University and University of Wisconsin at Madison Working Paper.

Ballester, J.M., Climent, F. and Furió, D., 2016. Market efficiency and price discovery relationships between spot, futures and forward prices: the case of the Iberian Electricity Market (MIBEL). Spanish Journal of Finance and Accounting/Revista Española de Financiación y Contabilidad, 45(2), pp.135-153.

Balcilar, M., Gungor, H. and Hammoudeh, S., 2015. The time-varying causality between spot and futures crude oil prices: A regime switching approach. International Review of Economics & Finance, 40, pp.51-71.

Balcilar, M., Gupta, R. and Pierdzioch, C., 2016. Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test. Resources Policy, 49, pp.74-80.

Bekiros, S.D. and Diks, C.G., 2008. The relationship between crude oil spot and futures prices: Cointegration, linear and nonlinear causality. Energy Economics, 30(5), pp.2673-2685.

BIS, 2019, Over the counter derivatives statistics at end-December 2018.

Black, F., 1976. The pricing of commodity contracts. Journal of financial economics, 3(1-2), pp.167-179.

Black, F., 1986. Noise. The journal of finance, 41(3), pp.528-543.

Black, D.G., 1986. Success and failure of futures contracts: theory and empirical evidence. Salomon Brothers Center for the Study of Financial Institutions, Graduate School of Business Administration, New York University.

Bodie, Z., Kane, A. and Marcus, A.J., 2018. Investments. McGraw-Hill Education.

Bohl, M.T., Salm, C.A. and Schuppli, M., 2011. Price discovery and investor structure in stock index futures. Journal of Futures Markets, 31(3), pp.282-306.

Breitung, J. and Candelon, B., 2006. Testing for short-and long-run causality: A frequency-domain approach. Journal of Econometrics, 132(2), pp.363-378.

Brooks, C., Rew, A.G. and Ritson, S., 2001. A trading strategy based on the lead–lag relationship between the spot index and futures contract for the FTSE 100. International Journal of Forecasting, 17(1), pp.31-44.

Brorsen, B.W. and Fofana, N.Z.F., 2001. Success and failure of agricultural futures contracts. Journal of Agribusiness, 19(345-2016-15191), pp.129-145.

Cagli, E.C., Taskin, D. and Mandaci, P.E., 2019. The short-and long-run efficiency of energy, precious metals, and base metals markets: Evidence from the exponential smooth transition autoregressive models. Energy Economics, 84, p.104540.

CBO, 2000. Chicago Board Options Exchange Margin Manual.

Chang, E.C., 1985. Returns to speculators and the theory of normal backwardation. The Journal of Finance, 40(1), pp.193-208.

Chen, A.S. and Lin, J.W., 2004. Cointegration and detectable linear and nonlinear causality: analysis using the London Metal Exchange lead contract. Applied Economics, 36(11), pp.1157-1167.

Chen R. and Zheng Z.L., 2008. Unbiased estimation, price discovery, and market efficiency: futures prices and spot prices. Systems Engineering-Theory & Practice, 28(8), pp.2-11.

Chen, P.F., Lee, C.C. and Zeng, J.H., 2014. The relationship between spot and futures oil prices: Do structural breaks matter?. Energy Economics, 43, pp.206-217.

Conrad, C. and Karanasos, M., 2010. Negative volatility spillovers in the unrestricted ECCC-GARCH model. Econometric Theory, 26(3), pp.838-862.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics, 7(2), pp.174-196.

Cox, J.C., Ross, S.A. and Rubinstein, M., 1979. Option pricing: A simplified approach. Journal of financial Economics, 7(3), pp.229-263.

Cox, J.C., Ingersoll Jr, J.E. and Ross, S.A., 1981. The relation between forward prices and futures prices. Journal of Financial Economics, 9(4), pp.321-346.

Dergiades, T., Madlener, R. and Christofidou, G., 2018. The nexus between natural gas spot and futures prices at NYMEX: Do weather shocks and non-linear causality in low frequencies matter?. The Journal of Economic Asymmetries, 18, p.e00100.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American statistical association, 74(366a), 427-431.

Diks, C. and Panchenko, V., 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics and Control, 30(9-10), pp.1647-1669.

Doran, J.S., Peterson, D.R. and Wright, C., 2010. Confidence, opinions of market efficiency, and investment behavior of finance professors. Journal of Financial Markets, 13(1), pp.174-195.

Engle, R.F. and Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica: journal of the Econometric Society, pp.251-276.

Fama, E.F., 1965. The behavior of stock-market prices. The journal of Business, 38(1), pp.34-105.

Fama, E.F., 1965. Random walks in stock market prices. Financial analysts journal, 21(5), pp.55-59.

Fama, E.F., 1991. Efficient capital markets: II. The journal of finance, 46(5), pp.1575-1617.

Fama, E.F., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of financial economics, 49(3), pp.283-306.

Fernandez, V., 2016. Further evidence on the relationship between spot and futures prices. Resources Policy, 49, pp.368-371.

Fleming, J., Ostdiek, B. and Whaley, R.E., 1996. Trading costs and the relative rates of price discovery in stock, futures, and option markets. Journal of Futures Markets: Futures, Options, and Other Derivative Products, 16(4), pp.353-387.

Galeotti, M., Lanza, A. and Manera, M., 2003. Rockets and feathers revisited: an international comparison on European gasoline markets. Energy economics, 25(2), pp.175-190.

Garbade, K.D. and Silber, W.L., 1979. Dominant and satellite markets: a study of dually-traded securities. The Review of Economics and Statistics, pp.455-460.

Garbade, K.D. and Silber, W.L., 1983. Price movements and price discovery in futures and cash markets. The Review of Economics and Statistics, pp.289-297.

Ghoddusi, H., 2016. Integration of physical and futures prices in the US natural gas market. Energy Economics, 56, pp.229-238.

Gong, C.C., Ji, S.D., Su, L.L., Li, S.P. and Ren, F., 2016. The lead–lag relationship between stock index and stock index futures: A thermal optimal path method. Physica A: Statistical Mechanics and its Applications, 444, pp.63-72.

Gonzalo, J. and Granger, C., 1995. Estimation of common long-memory components in cointegrated systems. Journal of Business & Economic Statistics, 13(1), pp.27-35.

Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, pp.424-438.

Grossman, S.J. and Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. The American economic review, 70(3), pp.393-408.

Guidolin, M. and Pedio, M., 2018. Essentials of time series for financial applications. Academic Press.

Gupta, S., Choudhary, H. and Agarwal, D.R., 2018. An empirical analysis of market efficiency and price discovery in Indian commodity market. Global Business Review, 19(3), pp.771-789.

Hansen, B.E. and Seo, B., 2002. Testing for two-regime threshold cointegration in vector error-correction models. Journal of econometrics, 110(2), pp.293-318.

Hao, J., Xiong, X., He, F. and Ma, F., 2019. Price Discovery in the Chinese Stock Index Futures Market. Emerging Markets Finance and Trade, pp.1-15.

He, L.Y. and Xie, W.S., 2012. Who has the final say? Market power versus price discovery in China's sugar spot and futures markets. China Agricultural Economic Review, 4(3), pp.379-390.

Hasbrouck, J., 1995. One security, many markets: Determining the contributions to price discovery. The journal of Finance, 50(4), pp.1175-1199.

Hiemstra, C. and Jones, J.D., 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation. The Journal of Finance, 49(5), pp.1639-1664.

Hossfeld, O. and Röthig, A., 2016. Do speculative traders anticipate or follow USD/EUR exchange rate movements? New evidence on the efficiency of the EUR currency futures market. Finance Research Letters, 18, pp.218-225.

Huang, B.N., Yang, C.W. and Hwang, M.J., 2009. The dynamics of a nonlinear relationship between crude oil spot and futures prices: A multivariate threshold regression approach. Energy Economics, 31(1), pp.91-98.

Hull, J.C., 2018. Options futures and other derivatives. Pearson Education Ltd.

Itô, K., 1951. On stochastic differential equations (No. 4). American Mathematical Soc..

Jebabli, I. and Roubaud, D., 2018. Time-varying efficiency in food and energy markets: Evidence and implications. Economic Modelling, 70, pp.97-114.

Jena, S.K., Tiwari, A.K., Hammoudeh, S. and Roubaud, D., 2019. Distributional predictability between commodity spot and futures: Evidence from nonparametric causality-in-quantiles tests. Energy Economics, 78, pp.615-628.

Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of economic dynamics and control, 12(2-3), pp.231-254.

Johansen, S., 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica: journal of the Econometric Society, pp.1551-1580.

Joseph, A., Sisodia, G. and Tiwari, A.K., 2014. A frequency domain causality investigation between futures and spot prices of Indian commodity markets. Economic Modelling, 40, pp.250-258.

Judge, A. and Reancharoen, T., 2014. An empirical examination of the lead–lag relationship between spot and futures markets: Evidence from Thailand. Pacific-Basin Finance Journal, 29, pp.335-358.

Junttila, J., Myllymäki, V. and Raatikainen, J., 2018. Pricing of electricity futures based on locational price differences: The case of Finland. Energy Economics, 71, pp.222-237.

Kahneman D. and Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica, 47(2), pp.263-291.

Kaldor, N., 1939. Speculation and economic stability. The Review of Economic Studies, 7(1), pp.1-27.

Kasman, A. and Kasman, S., 2008. The impact of futures trading on volatility of the underlying asset in the Turkish stock market. Physica A: Statistical Mechanics and its Applications, 387(12), pp.2837-2845.

Kawaller, I.G., Koch, P.D. and Koch, T.W., 1987. The Relationship between the S & P 500 Index and S & P 500 Index Futures Prices. Chicago Mercantile Exchange.

Kendall, M.G. and Hill, A.B., 1953. The analysis of economic time-series-part i: Prices. Journal of the Royal Statistical Society. Series A (General), 116(1), pp.11-34.

Keynes, J.M., 1930. Treatise on money.

Kissell, R., 2006. The expanded implementation shortfall: Understanding transaction cost components. The Journal of Trading, 1(3), pp.6-16.

Kosowski R. and Neftci S., 2015. Principles of financial engineering 3rd ed. Elsevier Inc..

Kummer, S. and Pauletto, C., 2012, May. The history of derivatives: A few milestones. In EFTA Seminar on Regulation of Derivatives Markets (pp. 431-466).

Kwiatkowski, D., Phillips, P.C., Schmidt, P. and Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of econometrics, 54(1-3), pp.159-178.

Lee, J.W., 2013. A comprehensive study on normal backwardations in futures markets. Journal of Accounting and Finance, 13(1), pp.115-121.

Lee, Y.H. and Mo, W.S., 2016. Analysis of price discovery and non-linear dynamics between volatility index and volatility index futures. Investment Analysts Journal, 45(3), pp.163-176.

Li, M.Y.L., 2009. The dynamics of the relationship between spot and futures markets under high and low variance regimes. Applied Stochastic Models in Business and Industry, 25(6), pp.696-718.

Lin, C.B., Chou, R.K. and Wang, G.H., 2018. Investor sentiment and price discovery: Evidence from the pricing dynamics between the futures and spot markets. Journal of Banking & Finance, 90, pp.17-31.

Lo, A.W., 2004. The adaptive markets hypothesis. The Journal of Portfolio Management, 30(5), pp.15-29.

Lo, A.W., 2007. Efficient markets hypothesis, in Durlauf, S.N. and Blume, L., 2nd ed., The new Palgrave dictionary of economics (Vol. 6). Basingstoke: Palgrave Macmillan.

Malkiel, B.G. and Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. The journal of Finance, 25(2), pp.383-417.

Malkiel, B.G., 2003. The efficient market hypothesis and its critics. Journal of economic perspectives, 17(1), pp.59-82.

Malkiel, B., Mullainathan, S. and Stangle, B., 2005. Market efficiency versus behavioral finance. Journal of Applied Corporate Finance, 17(3), pp.124-136.

Milunovich, G. and Joyeux, R., 2010. Market efficiency and price discovery in the EU carbon futures market. Applied Financial Economics, 20(10).

Moosa, I.A. and Al‐Loughani, N.E., 1995. The effectiveness of arbitrage and speculation in the crude oil futures market. Journal of Futures Markets, 15(2), pp.167-186.

Moosa, I.A., 1996. In: McAleer, M., Miller, P., Leong, K. (Eds.), An econometric model of price determination in the crude oil futures markets. Proceedings of the Econometric Society Australasian meeting, vol. 3. University of Western Australia, Perth, pp. 373–402.

Moreira Campos da Cunha Amarante, J.G., Bach, T.M., Vieira da Silva, W., Matiollo, D., Souza, A. and Pereira da Veiga, C., 2018. Econometric analysis of co-integration and causality between markets prices toward futures contracts: Evidence from the live cattle market in Brazil. Cogent Business & Management, 5(1), p.1457861.

Newberry, D.M., 1992. In: Newman, P., Milgate, M., Eatwell, J. (Eds.), Futures markets: Hedging and speculation. The new Palgrave dictionary of money and finance, vol. 2. Macmillan, London, pp. 207–210.

Nicolau, M. and Palomba, G., 2015. Dynamic relationships between spot and futures prices. The case of energy and gold commodities. Resources Policy, 45, pp.130-143.

Pati, P.C. and Rajib, P., 2011. Intraday return dynamics and volatility spillovers between NSE S&P CNX Nifty stock index and stock index futures. Applied Economics Letters, 18(6), pp.567-574.

Philip, D. and Shi, Y., 2015. Impact of allowance submissions in European carbon emission markets. International review of financial analysis, 40, pp.27-37.

Rittler, D., 2012. Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. Journal of Banking & Finance, 36(3), pp.774-785.

Samuelson, P.A., 1965. Proof that properly anticipated prices fluctuate randomly. Industrial Management Review, 6(2), pp. 41-49.

Schreiber, P.S. and Schwartz, R.A., 1986. Price discovery in securities markets. The Journal of Portfolio Management, 12(4), pp.43-48.

Schwert, G.W., 1987. Effects of model specification on tests for unit roots in macroeconomic data. Journal of monetary economics, 20(1), pp.73-103.

Schwert, G.W., 1989, Tests for unit roots: A Monte Carlo investigation, Journal of Business and Economic Statistics 7, 147-160.

Schwert, G.W., 2003. Anomalies and market efficiency. Handbook of the Economics of Finance, 1, pp.939-974.

Sensoy, A. and Hacihasanoglu, E., 2014. Time-varying long range dependence in energy futures markets. Energy economics, 46, pp.318-327.

Seo, B., 1999. Distribution theory for unit root tests with conditional heteroskedasticity. Journal of Econometrics, 91(1), pp.113-144.

Shao, Y.H., Yang, Y.H., Shao, H.L. and Stanley, H.E., 2019. Time-varying lead–lag structure between the crude oil spot and futures markets. Physica A: Statistical Mechanics and its Applications, 523, pp.723-733.

Shu, J. and Zhang, J.E., 2012. Causality in the VIX futures market. Journal of Futures Markets, 32(1), pp.24-46.

Silber, W.L., 1985. The economic role of financial futures. Salomon Brothers Center for the Study of Financial Institutes, Graduate School of Business Administration.

Silvapulle, P. and Moosa, I.A., 1999. The relationship between spot and futures prices: evidence from the crude oil market. Journal of Futures Markets: Futures, Options, and Other Derivative Products, 19(2), pp.175-193.

Simkins, B. and Jia, Y., 2016. Energy futures markets. In The World Scientific Handbook of Futures Markets (pp. 407-434).

Stoll, H.R., 1969. The relationship between put and call option prices. The Journal of Finance, 24(5), pp.801-824.

Theissen, E., 2012. Price discovery in spot and futures markets: A reconsideration. The European Journal of Finance, 18(10), pp.969-987.

Toda, H.Y. and Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. Journal of econometrics, 66(1-2), pp.225-250.

Torun, E., Chang, T.P. and Chou, R.Y., 2020. Causal relationship between spot and futures prices with multiple time horizons: A nonparametric wavelet Granger causality test. Research in International Business and Finance, 52, p.101115.

Tswei, K. and Lai, J.Y., 2009. Information contents misjudged: Digressive convergence to equilibrium in cointegrated prices. Review of Financial Economics, 18(4), pp.183-189.

Valkanov, R., 2005. Functional Central Limit Theorem approximations and the distribution of the Dickey–Fuller test with strongly heteroskedastic data. Economics Letters, 86(3), pp.427-433.

Wang, Y. and Wu, C., 2013. Are crude oil spot and futures prices cointegrated? Not always!. Economic Modelling, 33, pp.641-650.

Wang, D., Tu, J., Chang, X. and Li, S., 2017. The lead–lag relationship between the spot and futures markets in China. Quantitative Finance, 17(9), pp.1447-1456.

Weber, E.J., 2009. A short history of derivative security markets. In Vinzenz Bronzin's Option Pricing Models (pp. 431-466). Springer, Berlin, Heidelberg.

WFE, 2019, WFE IOMA 2018 Derivatives Report.

Wiener, N., 1956. The theory of prediction. Modern mathematics for engineers.

Wilson, B., Aggarwal, R. and Inclan, C., 1996. Detecting volatility changes across the oil sector. The Journal of Futures Markets (1986-1998), 16(3), pp.313-330.

Working, H., 1953. Futures trading and hedging. The American Economic Review, pp.314-343.

Xie, S. and Huang, J., 2013. Price discovery function of index futures in China: Evidence from daily closing prices. Economic and Political Studies, 1(2), pp.40-54.

Yan, Y. and Guiyu, Z., 2019. The empirical study on price discovery of cornstarch futures market in China. Applied Economics Letters, 26(13), pp.1100-1103.

Yang, L. and Zhang, D., 2013. Can futures price be a powerful predictor? Frequency domain analysis on Chinese commodity market. Economic Modelling, 35, pp.264-271.

Yao, C.Z. and Lin, Q.W., 2017. The mutual causality analysis between the stock and futures markets. Physica A: Statistical Mechanics and its Applications, 478, pp.188-204.

Zhang, Y. and Liu, L., 2018. The lead-lag relationships between spot and futures prices of natural gas. Physica A: Statistical Mechanics and its Applications, 490, pp.203-211.