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**THE LEAD-LAG RELATIONSHIP BETWEEN STOCK INDEX
FUTURES AND STOCK INDEXES**
Evidence from the US Stock and Futures Markets

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ABSTRACT

The belief that the stock index futures market leads the stock market is widely held. The majority of existing literature has found the futures market preceding the stock market. Furthermore, some have found evidence of the two markets moving contemporaneously. The aim of this thesis is to examine whether this lead-lag relationship exists between the stock index futures and their underlying stock indexes, and if so, in which direction does it move.

The focus of this thesis will be on the United States stock and futures markets. Two major stock indexes, Standard and Poor's 500 and Dow Jones Industrial Average, are chosen. The corresponding futures are SP and DJ, respectively. The data will consist of 5-minute intraday returns from a sample period of 8 months running from August 2008 to March 2009. The relationship between the two markets will be studied with Granger causality theorem and Vector Error Correction model.

The results show that there exists a two-way causal relation between S&P 500 and SP and DJIA and DJ. Furthermore, from the results it is also evident, inconsistent with the majority of the previous research, that there exists strong evidence of the two indexes leading the two futures. Additionally, a strong lead of SP over S&P 500 is also detected. Weak evidence of DJ leading DJIA is found. Furthermore, the lead-lag relationship seems more unstable than previous studies have found it to be.

The contemporaneousness of the data period and the global economic recessions is presumably the most important reason behind these surprising results. It is possible that during uncertain times, the stock market seems more tempting for the investors than the derivatives market. If speculators move away from the futures market during recession, as it proves too risky, hedgers who follow the stock market more closely may settle for a price under or over the market, thus inverting the lead-lag relationship. Additionally, the insecurity of the speculators might also in part explain why the lead-lag relationship is so unstable during the recession.

KEYWORDS: lead-lag relationship, futures contract, stock index, global recession

1. INTRODUCTION

The world has changed a great deal within the recent decades. That change and constant uncertainty about the future have also influenced the financial markets all around the world, making them unstable. This has for its part generated a large, rapidly growing demand for different derivative instruments; they can reduce risk by offering protection against unfavourable changes in the markets. Ironically, some have blamed derivatives for unbalancing the world even further. Futures contracts, probably the most popular derivatives instruments in the world, have a very significant role as investment hedgers. Initially, futures markets were introduced to eliminate risk for commodities and were basically designed only for agricultural products. Since then futures markets have exploded. (Chicago Mercantile Exchange, CME 2009.)

Originally, there were some rice agreements in Japan already in the 16th century that were similar to present-day forward contracts, but the first modern market for futures, however, was the Chicago Board of Trade (CBOT). It began trading wheat contracts in the 1860s. At first the contracts were only forwards but as their popularity grew, they were often changed to more standardized forms in order to speed up the trade process. These standardized contracts were essentially the first futures contracts. (CME 2009.)

Important progress was made in 1971 when the first financial futures were introduced. First they were only underlying currency rates. But as the market for them grew and also gained creditability from the support of acknowledged economists, it was only a matter of time that other instruments would follow. This unsurprisingly led to the introduction of futures underlying interest rates in 1976. This was also when another crucial improvement to futures markets was made. Instead of having to physically settle the futures at maturity with the exchange of the underlying goods, a new form of settlement was developed where the futures were settled with cash. Cash settlement eliminated the difficulty of physically delivering the underlying items, thus expanding the range of products upon which futures could feasibly be traded. This futures market evolution resulted in stock index futures in 1982, the first one having Standard & Poor's 500 index (S&P 500) as the underlying item. In the early 1980s, the stock indexes had become the barometers of the overall health of the stock markets, and stock index futures drew an immediate demand because they enable investors to trade the values of the market without having to own any individual shares. Moreover, stock index futures are appealing also in that they are less costly and easier to trade than hundreds or even thousands of individual shares. (CME 2009.)

1.1. Preview of Previous Studies

This thesis examines the relationship between the returns of stock index futures and the returns of their underlying stock indexes. This research area has been well covered by several respected economists and a significant body of literature has evolved (see e.g. Herbst, McCormak and West 1987; MacKinley and Ramaswamy 1988; Lo and MacKinley 1990; Stoll and Whaley 1990; Chan, Chan and Karolyi 1991; Chan 1992; Fleming, Ostdiek and Whaley 1996; Brooks, Garret and Hinich 1999; Frino, Walter and West 2000; Jiang, Fung and Cheng 2001; Chatrath, Christie-David, Dhanda and Koch 2002). Previous research generally suggests that there is strong evidence that stock index futures returns lead the returns of stock indexes (e.g. Herbst et al. 1986), and a weak evidence that the stock index price movements lead the price movements of their corresponding futures (e.g. Stoll and Whaley 1990; Chan 1992). However, some studies question the lead-lag relationship entirely, claiming that previous studies are biased (Brooks et al. 1999).

1.1.1. Magnitude and Reasons for the Lead-Lag Relationship

One of the first studies on the leads and lags of futures prices and spot prices, Herbst et al. (1987), examined price changes over 10 seconds periods. Data consisted of S&P 500 futures prices and index prices over a period of one month in 1982, and Value Line Composite Index (VLCI) futures prices and index prices over a four-month period in 1982. The study found a strong contemporaneous relationship between spot and futures returns, but also evidence suggesting that the futures markets lead the stock markets by a few minutes. Herbst et al. believed the lead of futures might explain the volatility in the stock index futures basis, and vice versa, as the lead tends to occur when anticipating the direction of movements of the basis. Meanwhile, MacKinley and Ramaswamy (1988) argued that if the analysed time period is too short, the futures and spot prices tend to move with autocorrelation. They examined the S&P 500 futures and the underlying index over a 15-minute period and discovered problems of autocorrelation due to nonsynchronous trading of the stocks in the index. However, extending observation intervals to 60 minutes, little evidence of the problem remained.

Lo and MacKinley (1990) had similar results, finding evidence to support the lead of futures prices over the spot prices. They also further examined the nonsynchronous trading of the stocks in the index and attributed most of the lead-lag relationship to it.

They argued that the futures prices only lead those stocks in the index with higher nontrading possibilities than the futures themselves, and showed strong evidence of the nonsynchronous trading being the sound reason for the lead of the futures.

Stoll and Whaley (1990) studied the returns of S&P 500 index and Major Market Index (MMI) futures over 5-minute periods from 1982 to 1987. Their findings were somewhat mixed. They came across a strong contemporaneous relationship between the returns of futures and stocks for both indexes, but also found that the futures returns lead the stock returns from 5 up to 10 minutes. From previous studies they recognized the evidence of the nonsynchronous trading as one factor for the futures lead, but used an autoregressive moving average (ARMA) model to extract the bid/ask price effects and infrequent trading effects. Therefore, any remaining lead of the futures returns had to be due to the price discovery role of the futures markets. Furthermore, they also discovered that futures returns also lead the returns of very actively traded stocks in the index, further dismissing the nonsynchronous trading as sole cause for the lead of the futures market over the stock market, dismissing the findings of Lo and MacKinley (1990).

However, Chan et al. (1991), while studying the intraday relationship between price changes and price change volatility in the S&P 500 stock index and the corresponding futures markets from 1984 to 1989, had contrary findings to previous studies. Although they found futures returns in fact leading the stock returns by an average of 5 minutes, they also argued that when focusing on the volatility of price changes between futures and spot markets, it can be shown that price discovery originates not only from the futures markets but from the stock market as well. They stated that both markets serve important price discovery roles, slightly questioning the previous studies. They used a generalized autoregressive conditional heteroskedasticity (GARCH) model and admitted that although being able to control potential market frictions, their findings were robust.

Chan (1992) returned to the lead-lag relationship of futures prices and stock prices with similar results. While investigating the MMI between 1984 and 1985 and again in 1987, he further stated that regardless of an apparent asymmetric lead-lag relationship between the two markets, nonsynchronous trading is not by any means an adequate explanation for it. He continued that in addition to strong evidence for futures leading the stock index, there is also weak evidence for the stock index leading the futures. Chan disputed the infrequent trading with on grounds. First, an asymmetric lead-lag holds for all component stocks even in 1984–1985, when some of the stocks in MMI

where more frequently traded than the futures, and second, the returns of some of the very actively traded stocks in MMI, with nontrading possibilities close to zero, still lag the futures returns significantly.

Chan (1992) also viewed the lead-lag relationship under good news versus bad news and under relative intensity, and found no evidence of either affecting the lead-lag. He then stated that the lead-lag relationship varies greatly with the extent of market-wide information. When there is new systematic (market-wide) information, causing more stocks to move together, the feedback from the futures market to the stock market strengthens. This supports the hypothesis that the stock market and the futures market do not have equal access to new information. Since the stock-specific information is unsystematic and the systematic information can be regarded more important, the feedback from the futures markets to the stock market is stronger than the reverse. To summarise, Chan explains the lead-lag relationship with two interrelated reasons, the ability of futures to process information faster than stocks, and futures' capacity to better reflect the systematic information.

Meanwhile, Shyy, Vijayraghavan and Scott-Quinn (1996), who investigated the CAC 40 index and the corresponding CAC index futures for a one-month period in 1994, disputed some of the previous work. Even though they used an error correction model (ECM) to remove autocorrelation, they could not solve the nonsynchronous trading problem, consequently noticing that the lead-lag relationship vanishes. They simply stated that previous results showing futures leading the stock markets were primarily due to nonsynchronous trading, stale price problems and differences in trading mechanisms used in the stock and the futures markets.

The above research direction received some support from Brooks et al. (1999), who questioned the entire existence of the lead-lag relationship when investigating the daily returns of futures and indexes for S&P 500 from 1983 to 1993 and for FTSE 100 from 1985 to 1995. They argued that when assuming that the underlying data generating process is constant, previous studies, or especially the tests they have used in detecting a strong lead-lag relationship for the futures markets and the spot markets, might be prone to overstate their findings. The study used another test, called the Hinich test¹, and found, contrary to results from using the traditional methodology, that periods where the

¹ The Hinich test for gaussianity is really a test of the null hypothesis that the bispectrum is zero for all bifrequencies and thus if the Hinich test rejects the null hypothesis then the ARCH/GARCH specification is falsified for any set of model parameters. For more, see Brock (1987).

futures market leads the stock market are few and far between and when any lead-lag relationship is detected, it does not last long. Moreover, the study ended with futures markets and stock markets moving together, very contemporaneously.

Chiang and Fong (2001) examined the futures market returns and the stock market returns on the Hang Seng Index (HSI) based in Hong Kong. Their intraday data was from a nine-month period in 1994. The research used a model similar to GARCH to remove the autocorrelation effects from the stock returns and found that the futures market in fact leads the stock market, but only before the autocorrelation effects are purged, not after. This result was thought to arise because even though HSI is a capitalization-weighted index, it is still heavily affected by a few major stocks. Consistent with this conclusion the research shows that these major component stocks have a more or less symmetric lead-lag relation with the futures. Furthermore, the study attributed the futures' lead to price discovery and offered an interesting argument: because the study also examined the returns of HSI options and did not detect any lead they might have over the stock market, the research concluded that the relative informational efficiency on emerging markets seems to depend on the market maturity, as the HSI futures market is far more mature than the HSI options market.

In another interesting study directed at the HSI stock and futures markets, Rajaguru and Pattanayak (2007) emphasize on the research methods and compare the different models with which the lead-lag relationship can be inspected. They compare three models, vector autoregression (VAR), ECM and the fractionally integrated error correction model (FIECM), which is a modification from ECM designed for two series that are fractionally co-integrated (see Engle and Granger 1987). As the study tries to evaluate both long-term and short-term lead-lag relationship, the data used is quite impressive, running from 1988 to 2001. The study shows that fractionally co-integrated models are essential in financial forecasting, as FIECM provides by far the best results for the unidirectional long memory nature of the lead-lag, and thus outperforms the competitive models. Overall, however, ECM provides best performance in the short-term forecasts. These results can be seen to be consistent with the price discovery hypothesis (cf. e.g. Chan 1992).

Brooks, Rew and Ritson (2001) study ten-minute observations of FTSE 100 index prices and its index futures prices from 1996 to 1997. They found, unsurprisingly, that the futures market leads the spot market, and that this predictive power of futures returns supports the hypothesis that new systematic information disseminates first in the

futures market and then in the stock market, with arbitrageurs trading across both markets to maintain the cost of carry relationship. Particular about this rather straightforward study was that Brooks earlier argued against the entire existence of the lead-lag relationship (cf. Brooks et al. 1999).

Alexakis, Kavussanos and Visvikis (2002), while focusing on the futures and stock market of the Athens Stock Index (ASE), and more closely on the FTSE/ASE-20 index from 1999 to 2000 and the FTSE/ASE Mid-40 index from 2000 to 2001, encountered similar results. They used a GARCH model and some of its variations and found evidence that futures prices lead the stocks prices. They point to the price discovery hypothesis and state that futures prices contain useful information about the subsequent stock prices, beyond that already embedded in the current stock price, and can therefore be used as price discovery vehicles.

The most recent studies investigating the lead-lag relationship have been quite unanimous about the existence of and reasons for the phenomenon, regardless of where they have been conducted. Zhong, Darrat and Otero (2004) examined the Mexican Price and Quotation Index (IPC) and the corresponding futures from 1999 to 2002, and found that futures serve as useful price discovery vehicles, but can also be a source for instability for the spot market. Furthermore, Nam, Oh, Kim and Kim (2006) used minute-by-minute price data from 2001 to 2003 to investigate the KOSPI 200 index, listed in Korea Stock Exchange (KSE), and the corresponding futures. They came across evidence suggesting that futures prices lead those of the stock index by an average of 23 minutes, price discovery hypothesis being the main influence. They also mention, consistent with some previous studies (cf. e.g. Fleming et al. 1996), lower transaction costs and better leverage as secondary reasons for the futures lead. Finally, Ramasamy and Shanmugam (2007) studied the closing prices of Kuala Lumpur Stock Exchange Composite Index (KLSECI) and its futures (FKLI) from 1995 to 2001. They argue that a one-day lead of the futures markets exists, and that it strengthens under high volatility in both markets. However, they add that a contemporaneous relationship between the two markets also exists and that the stock and futures prices are very co-integrated.

1.1.2. Behaviour and Nature of the Lead-Lag Relationship

While analysing the intraday price change volatility of S&P 500 index futures from 1982 to 1990, Chang, Jain and Locke (1995) came across an interesting discovery. They noticed that, as the New York Stock Exchange (NYSE), where the stocks of the index are traded, was about to close, there were significant changes in the behaviour of the futures prices. During most of the day, the S&P 500 futures price volatility follows a U-shaped pattern, consistent with findings in the equities markets. Futures' volatility declines prior to the NYSE close, reflecting a similar decline in stock index volatility. However, as NYSE closes, there is still a 15-minute time period to trade the index futures (the S&P 500 index futures are not traded at NYSE but in CME). The original intent for this 15-minute cushion is to allow for slow reporting of trades from NYSE. What the researchers noticed is that after NYSE closes the price volatility of index futures forms a small U-shaped pattern. In particular, futures trading rises towards a peak in the final minute of trading. Since the trading mechanisms are different (NYSE and CME), this phenomenon cannot be attributed to the institutional factor in the stock market; instead the phenomenon appears to be more widespread. It seems that the price discovery of the futures markets, and thus the lead-lag relationship, continues even in the absence of organized trading for the underlying stock market.

Fleming et al. (1996) look more closely at transaction costs while examining the S&P 500 and the Standard and Poor's 100 (S&P 100) indexes and their futures from 1988 to 1991. An ARMA process was used to exclude the biased autocorrelation of the prices. They stated that as the cost for trading index futures is about 3% of the cost of trading equivalent stock portfolio, investors with market-wide knowledge are drawn to trade futures instead of spot, thus causing the futures market to precede the stock market. This is in line with the price discovery hypothesis. They further noted that despite the lead, the contemporaneous relationship between futures prices and spot prices has grown over time.

Frino et al. (2000) examined one-minute returns on the All Ordinaries Index² (AOI) and the Share Price Index² (SPI) futures between 1995 and 1996. They focused on the price movements around macroeconomic and stock-specific news releases and used an ARMA model to remove undesired frictions in the prices. What they discovered is that

² The SPI is based upon the AOI and is traded in the Sydney Futures Exchange (SFE). All the stocks of AOI are traded in the Australian Stock Exchange (ASX).

futures lead the stock market by some minutes. As for the behaviour of the relationship between the two prices around the news releases, their results were unsurprising, as they found the lead of futures strengthening when systematic information (macroeconomic) was introduced, and the lead of the futures weakening when unsystematic information was declared. Furthermore, they added that the weakening of the lead is not as significant and strong as the strengthening. Their findings are very much in line with previous studies concerning the behaviour of the lead-lag relationship around new information releases (e.g. Stoll and Whaley 1990, Chan et al. 1991 and Chan 1992).

The idea that short-selling restrictions in stock markets further signify the lead of futures markets over the stock markets was investigated by Jiang et al. (2001), as they examined the lead-lag relationship under three different short-selling regimes for the HSI and its futures from 1993 to 1996. Their results indicate that lifting the short-selling restrictions for stock can enhance both the informational efficiency of the stock market and the joint pricing efficiency of the stock and the futures markets. Furthermore, when restrictions are lifted, the contemporaneous price relationship is strengthened to a greater extent for a falling market and for negative mispricings (cf. Chan 1992). Therefore, lifting short-selling restrictions does reduce the lead-time of futures over spot, especially in a falling market situation.

Similar findings were made by Chatrath et al. (2001) when they analysed 15-minute returns for the S&P 500 from 1993 to 1996. Their focus was on the circumstances under which futures lead the spot. They suggest that the nature of the lead-lag relationship between futures and spot, and also between basis and volatility, depends, partly, on the predisposition of commercial traders to select index trading over stock trading when the markets are rising. They also added that when volatility is high, and the market is not at the open or the close, futures' lead is the strongest. Their findings are in line with Jiang et al. (2001), although slight nuance differences on the hypothesis that when markets fall, the contemporaneous price movement of the two strengthens, do appear.

When investigating the effects of modern trading on the lead-lag relationship of futures and spot, Frino and McKenzie (2002) came across rather surprising results. They studied the FTSE 100 index and its futures for a 5-month period in 1999, using LIFFE CONNECT screen trading system for both futures and stocks. They found that this weakens the lead-lag relationship and strengthens the contemporaneous movements of the prices. This evidence differs from that of the previous literature as the introduction of LIFFE CONNECT improved the attractiveness of futures markets as a origin of new

information, which should strengthen the lead-lag and not vice versa. The reason for this difference in results is most likely a reflection of the fact that the stock market was generally floor traded in the previous literature, while in this study the FTSE 100 was screen traded.

1.2. Purpose of the Study, Hypotheses and Thesis Structure

This study investigates the relationship between the S&P 500 and Dow Jones Industrial Average (DJIA) indexes and their corresponding futures SP and DJ. From the large field of empirical studies and findings explained above, the research hypotheses can be derived. First, a distinct presumption that stock index futures prices and the stock index prices are related can be formed. Further, the relation seems to, like shown in many studies above, have features suggesting that one of the prices precedes the other, forming a lead-lag relationship. Therefore, quite conceivably, the two first hypotheses are as follows.

H₁: S&P 500 index returns and the SP futures returns have a lead-lag relationship.

H₂: DJIA index returns and the DJ futures returns have a lead-lag relationship.

Now, if H₁ and H₂ would be rejected, it would mean that stock index futures prices and stock index prices always move contemporaneously. Studies indicating this result are an apparent minority (e.g. Brooks et al. 1999). Moreover, if we continue from the assumption that H₁ and H₂ are accepted, another clear presumption made from the empirical research is that the futures prices lead those of the stock indexes. This is hypothesized as follows.

H₃: S&P 500 index returns lead the SP futures returns.

H₄: DJIA index returns lead the DJ futures returns.

Therefore, if H₁ or H₂ would be accepted and H₃ or H₄ rejected, it would mean that the returns of at least one of two stock indexes lead the returns of the corresponding stock

index futures, and not vice versa. Some studies have found weak evidence suggesting this (e.g. Chan 1992), but in the vast majority of research the lead-lag relationship runs from the futures market to the stock market.

The remainder of this thesis contains four sections in the following order: theoretical, descriptive, empirical and conclusive. The next two chapters constitute the theoretical segment. They summarise the theory of futures and stock indexes and also explain the principals of futures pricing. They also refocus on the concept of stock index futures and further construe its properties and attributes. Chapter four focuses on the research data and the methodology with which it is going to be studied. Chapter five contains the empirical analysis and results arising from the data. The last chapter summarises and concludes the work the thesis has achieved.

2. THEORY OF FUTURES

Futures contract is an agreement between two parties to buy or sell an asset for a certain price at a certain point in time. The investor who buys the contract assumes long position as the seller assumes short position, respectively. Futures contracts are standardized and normally traded through an exchange, which mainly distinguishes them from their close counterparts, forward contracts. Furthermore, another distinguishing characteristic is that unlike forwards, futures do not usually have an exact delivery date. Futures also next to never lead to a delivery, but are instead closed out prior to their maturity. Futures are traded very actively around the world and a very wide range of commodities and financial instruments form the underlying assets in the various contracts. These include e.g. wheat, grain, sugar, gold, copper, tin, oil, currencies, Treasury bonds and stock indexes. The largest futures exchanges in the world include Chicago Mercantile Exchange (CME), CBOT, Eurex, London Financial Futures and Options Exchange (LIFFE), Tokyo international Financial Futures Exchange (TIFFE) and Singapore International Monetary Exchange (SIMEX). (Sharpe, Alexander and Bailey 1999:654–655; Bodie, Kane and Marcus 2002: 739–745; Hull 2003: 19–39.)

Futures trading provides two kinds of strategies in which futures can be traded in: they can be used in hedging and in speculating purposes. Speculators buy and sell futures for the sole purpose of closing out their positions at a better price than the initial price, in order to make a profit. It's never even their intention to either produce or use the underlying assets of the futures contract. In contrast, hedgers buy and sell futures to reduce market exposure and thus offset an otherwise risky position. In the ordinary course of business their intention is to either produce or use the underlying assets. (Sharpe et al. 1999: 654; Bodie et al. 2002: 752–787.)

Stock index futures are always settled in cash because delivering a portfolio of hundreds of shares would be very difficult and costly. The most popular underlying indexes for stock index futures include S&P 500, DJIA, NASDAQ 100, Nikkei 225, CAC-40, DAX-30, FTSE 100 and DJ Euro Stoxx 50. They are traded daily worldwide and have large open interests. (Bodie et al. 2002: 744– 750; Hull 2003: 53–54.)

2.1. Introduction to Futures Contract

Futures contracts are traded in organized exchanges and are therefore always standardized contracts. The key role of the exchange is to organize trading so that contract defaults are avoided. Moreover, the exchange must define carefully the precise nature of what is traded (the asset), how large are the quantities (the contract size), the daily procedures that will be followed (mark to market), the delivery arrangements, (the delivery months and the settlement) and also the regulations that will govern the market (limits). (Sharpe et al. 1999: 654–687; Bodie et al. 2002: 740–795; Hull 2003: 19–38.)

When the asset underlying a futures contract is a commodity, there can be a large variation in the quality available in the marketplace. As the asset is specified, it is therefore important for the exchange to determine the grade or the grades that are acceptable upon delivery. For some commodities a range of grades can be accepted, but the price depends on the grade chosen for delivery. The financial assets underlying futures are generally already well defined by nature and very unambiguous, thus requiring little or no grade determination. (Bodie et al. 2002: 749; Hull 2003: 20–21.)

The *contract size* specifies the quantity of the asset underlying one futures contract. This is an important feature for the investors. If the contract size is too small, trading in large positions can prove to be costly as there are transaction costs associated with each contract traded. In contrast, a too large contract size prevents investors from hedging relatively small exposures. The suitable contract size depends mostly on the likely investor, meaning that agricultural futures have much smaller contract sizes than financial futures, for example. (Bodie et al. 2002: 773–774; Hull 2003: 21.)

Perhaps the most important function in avoiding contract defaults is the *mark to market* feature. It basically means that the futures are settled daily, and money transfers between the market participants accordingly. This prevents the investors from backing out from the agreements or not having the financial recourses to honour them. In order to take a position in futures, the investor has to deposit an *initial margin* to a specified *margin account*. The initial margin is by no means the payment for the futures, but rather insurance that the contract will be honoured. When the price of the futures contract fluctuates over time, the open position will be calculated daily, and the investor's gain or loss is either added to or subtracted from the margin account, bringing the value of the contract back to zero. If the balance on the margin account will drop below an initially agreed limit, known as the *maintenance margin*, the exchange will

issue a *margin call* to the investor, who is then expected to top up the margin account balance to the initial margin level. This amount deposited is known as the *variation margin*. If the investor fails to provide the variation margin, the position will be closed. The marking to market process is one of the key features separating futures from forwards, which are settled only at maturity rather than daily. (Sharpe et al. 1999: 656–665; Bodie et al. 2002: 747–749; Hull 2003: 24–27.)

The exchanges outsource all the mark to market, reconciliation and settlement functions to a third party, usually referred to as the *clearinghouse*. The clearinghouse member becomes the seller's buyer and buyer's seller and interacts directly with the market participants. Furthermore, the clearinghouse member has to also maintain a margin account with the clearinghouse, known as the *clearing margin*. (Sharpe et al. 1999: 658–659; Bodie et al. 2002: 744–746; Hull 2003: 24–26; Sutcliffe 2006: 21–22.)

The place and time for the delivery must be specified by the exchange. The delivery place is important for commodity futures and particularly those requiring significant transport costs. The delivery time, or the *maturity* of a futures contract, must also be stipulated by the exchange. Futures contracts are referred to by their *delivery months*. The delivery months vary from contract to contract and are chosen to meet the needs of the market participants. For example, the main delivery months for stock index futures are March, June, September, and December. For many futures, the delivery period is the whole month. The exchange must also set the date when the trading for a particular futures contract begins and most importantly when it ends. The *last trading day* for futures is usually the third Friday or the fourth Wednesday of the delivery month. Futures contracts always trade for closest the delivery month and a number of coming delivery months. (Sharpe et al. 1999: 656–665; Bodie et al. 2002:749; Hull 2003: 22.)

Although very few of the futures contracts lead to the delivery of the underlying asset, it is nevertheless important to agree on specific terms for the delivery. The decision on when to deliver is made by the investor with the short futures position, who declares willingness to deliver, and in the case of commodities, also the place and grade of the delivery to the exchange clearinghouse. This is called the *notice of intention to deliver*. This notice cannot be issued prior to a specified day, agreed upon when the contract was made. It is known as the *first notice day*. When the clearinghouse receives the notice, they pass it to an investor with a long position to accept delivery. Common practice is that the clearinghouse chooses the investor with the oldest outstanding position. Investors with long positions are always forced to accept deliveries, or they have to

quickly find another investor with a long position prepared to take the delivery instead of them. If the investor with the long position wishes to avoid delivery, he or she should close out the position prior to the first notice day. This whole procedure from the notice to the actual delivery generally lasts two or three days. (Bodie et al. 2002: 749; Hull 2003: 31–32.)

The introduction of financial futures generated another way to settle futures contracts, known as the *cash settlement*. The cash settlement means that rather than the actual underlying assets being delivered, a cash amount equalling the value of the asset is delivered instead. Cash settlement is used for e.g. stock index futures. Delivering the underlying asset would mean delivering a portfolio of hundreds of shares, which would be inconvenient as well as impractical or even impossible. When a futures contract is settled in cash, it is simply marked to market in the last trading day and all the positions are closed. (Bodie et al. 2002: 749; Hull 2003: 32.)

National trading committees regulate futures markets. All new contracts and all changes to existing contracts have to be approved by the committees. In order for a contract to be approved it has to hold some useful economic purpose. The trading committees are responsible for the futures prices to be well communicated and transparent, and they also oversee the licensing of futures trading providers. The trading committees have authority over the exchanges and can force them to take disciplinary action against members who violate the trading rules. The trading committees also set the *price limits* within which a certain futures price may fluctuate during a trading day. Price limits are viewed as means to limit violent price movements. They are often eliminated as contracts approach maturity. (Sharpe et al. 1999: 663–664; Bodie et al. 2002: 749–750; Hull 2003: 33–34; IOSCO 2009.)

2.1.1. Payoff for Futures Contracts

Futures contract always has two participants, the investor who agrees to buy and the investor who agrees to sell. The buyer takes a *long position* and the seller assumes *short position*. If we look at the payoff for a futures contract, the buyer profits when the price of the futures increases and vice versa. More generally, the long position makes money when the price goes up and short position makes money when the price goes down. (Sharpe et al. 1999:665; Hull 2003: 2–5.)

The payoff for a futures contract is the value of the position at maturity. Therefore, the payoff to a long futures contract is

$$(1) \quad S_T - K,$$

where K is the delivery price and S_T is the spot price of the asset at maturity. This is because the holder of the contract is obligated to buy an asset worth S_T for K . Similarly, the payoff to a short futures contracts is

$$(2) \quad K - S_T$$

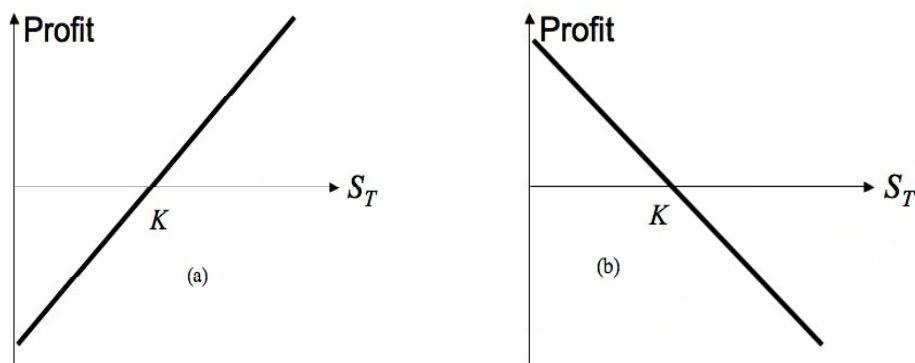


Figure 1. Payoffs from (a) long position and (b) short position. K = Delivery price and S_T = price of the asset at maturity.

These payoffs can be positive or negative. One has to bear in mind, however, that in an actual trading situation these diagrams do not apply for futures because they ignore marking to market. Rather, these diagrams state the payoffs from forward contracts. However, the same theory can be used to explain futures contract payoffs as well. (Hull 2003: 3–4; Sutcliffe 2006: 34–35.)

2.1.2. Convergence of Futures Price to Spot Price

As the expiry of a futures contract approaches, the futures price converges to the spot price of the underlying asset. At maturity, the futures price equals the spot price. This occurs because of the arbitrage arguments. If, for example, the futures price is above the spot price during the delivery period, investors have a clear arbitrage opportunity by shorting a futures contract and buying the underlying asset, then making the delivery.

These kinds of actions are destined to lead to a fall in the futures price. Furthermore, if the futures price is below the spot price, investors can buy futures contracts and just simply wait for the delivery to be made, thus raising the futures price. (Hull 2003: 23–24; Sutcliffe 2006: 155–158.)

This results in the futures prices being very close to the spot price during the delivery period. This feature is known as *co-integration*. There have been several empirical studies proving strong co-integration between futures price and spot price. The situation is illustrated in Figure 2. The circumstance under which this pattern is observed is viewed more closely later. (Hull 2003: 23–24; Sutcliffe 2006: 155–158.)

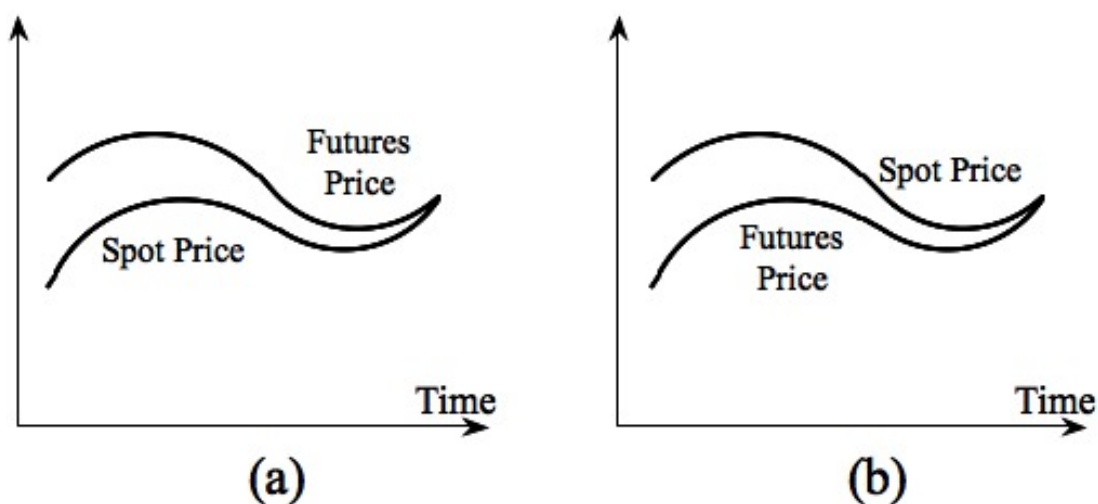


Figure 2. Relationship between futures price and the spot price as the delivery period is approached. (a) Futures price above spot price; (b) futures prices below spot price.

2.1.3. Determination of Futures Prices

When determining the theoretical price for a futures contract it is essential to understand the relation between forward prices and futures prices. As forwards do not have a daily settlement but are rather settled with a single payment at maturity, they are much easier and more functional to analyse. Therefore, the following price and analysis is in fact for forwards. Fortunately, it can be shown that when the risk-free interest rate is constant and same for all maturities, the price of a forward contract and a futures contract with the same maturity is equal (Cox, Ingersol and Ross 1981). (Hull 2003: 41–52; Sutcliffe 2006: 19–113.)

Furthermore, another fundamental observation needs to be made. By using arbitrage arguments the forward and the futures price of an *investment asset* can be determined by observing various market variables. This cannot be done, however, for the forward and the futures price of a *consumption asset*. An investment asset is an asset that is held primarily for investment purposes. Examples of an investment asset are bonds, stocks and gold. A consumption asset is an asset held mainly for consumption. Such commodities as oil, copper and wheat are examples of consumption assets. The properties of these two asset categories have to be acknowledged and a clear segregation between them needs to be made in order to derive any price theories for forwards and futures. (Hull 2003: 41; Sutcliffe 2006: 19–33.)

The simplest futures contract to value is one underlying an asset that provides the holder no income, e.g. a zero-coupon bond and a non-dividend-paying stock. If the price of an underlying asset is S_0 , the constant risk-free interest rate is r , and time to maturity is T , then the price of future, F_0 , is

$$(3) \quad F_0 = S_0 e^{rT}$$

Another way of illustrating equation (3) is to consider the following: if investor buys one unit of underlying asset at a price S_0 and enters into a short futures contract to sell it for F_0 at time T , the cost will be S_0 and it is certain to lead to a cash flow of F_0 at time T . Consequently, S_0 must equal the present value of F_0 . This means that

$$(4) \quad S_0 = F_0 e^{-rT},$$

which is equivalent to equation (3). Now, if $F_0 > S_0 e^{rT}$, investors can buy the asset and short futures underlying the asset, making arbitrage for an amount equal to $F_0 - S_0 e^{rT}$, and thus raising the price of the asset. Moreover, if $F_0 < S_0 e^{rT}$, investors can correspondingly short the asset and buy a futures contract on it, arbitraging the profit equal to $S_0 - F_0 e^{-rT}$. This would then result in a rise in the price of the futures contract. Therefore, by arbitrage arguments, if either of the two previous situations should exist, the arbitraging actions of investors would lead to equalising prices and eliminating the arbitrage opportunity. In other words, it would lead to equation (3). (Wilmott, Howison and Dewynne 1995: 98–100; Hull 2003: 41–46; Sutcliffe 2006: 53–54.)

At maturity the futures price equals the spot price. Therefore,

$$(5) \quad F_T = S_T,$$

when F_T is the futures price at maturity and S_T is the spot price at the expiry of the futures contract. This is obvious because an investor with a long futures position can obtain immediate delivery of the asset with price F_T . If $F_T \neq S_T$, risk-free arbitrage would be possible. If we derive a natural logarithm from equation (3), we get

$$(6) \quad \ln F = \ln S + rT$$

It means that if, r is constant, and the futures contract is close to maturity, which means T hardly changes, then relative changes in S result as the same relative changes in F . This means that futures price and spot are not only co-integrated, like shown before, but their correlation is also close to one near maturity. This is the foundation for the popularity of using futures to hedge a position in the underlying, which is discussed more closely later. (Baz and Chacko 2004: 57–61; Sutcliffe 2006: 155–158.)

The previous pricing model was for futures underlying assets that provide no income. Next we consider a futures contract on an asset providing perfectly predictable cash income for its holder. Good examples of these kinds of assets are stocks paying known dividends and coupon-bearing bonds. The notation is the same as earlier and we introduce I as the present value of income. We get

$$(7) \quad F_0 = (S_0 - I)e^{rT}$$

This equation is in line with (3) and applies to any asset that provides known cash income. One has to bear in mind, however, that I is only theoretical and many times it can be difficult to predict the precise amount of the future income, for example future stock dividends, if the time to maturity is long. But at the same time, it has been proven that because the time period between the dividend ex-date and payment date is long, and because the majority of the trading of a certain futures contract takes place relatively close to its maturity, even large variations in dividends only results in minor changes in the futures price (Yadav and Pope 1990 and 1994). This means that the futures price is largely unaffected by the estimates of dividends used in the calculations. Hence, the income certainty assumption is rather insignificant, at least when pricing futures underlying dividend-paying stocks. (Hull 2003: 47–49; Sutcliffe 2006: 119.)

The situation where the futures underlying asset provides a known yield rather than a known income requires yet another pricing formula. If we suppose that an asset is expected to pay a known yield to its holder we can look for example at a stock index future. A stock index can be regarded as the price of an asset that pays dividends. The asset is the portfolio of stocks constituting the index, and the dividends paid by the asset are the dividends the holder of the portfolio would receive. Furthermore, the dividends are often considered to provide a known yield rather than known cash income. Again, the notation remains unchanged and we implement q as known yield, thereby getting

$$(8) \quad F_0 = S_0 e^{(r-q)T}$$

Like I , q is only theoretical and can also be difficult to predict precisely. For example the dividend yield for a stock portfolio varies significantly throughout the year. Therefore, the chosen value of q should be the average annualized yield during the life of the futures contract. For stock index futures this means using those dividends which have their ex-dividend date during the life of the contract, when estimating q . It should also be mentioned that the results of (8) can vary slightly depending on what *compounding frequency* is used for q . The most common ones are *annual compounding* and *continuous compounding*. (Sharpe et al. 1999: 676–681; Bodie et al. 2002: 774–780; Hull 2003: 49–54; Sutcliffe: 127–143.)

If we derive the concept of known yield further, it is rational to examine currency futures next. As the exchange rates between currencies are persistently under substantial variation, currency futures are an important form of protection against undesired exposure to it. Hence, a model for pricing currency futures follows next. The underlying asset in a currency futures contract is a certain number of units of foreign currency. That means that S_0 is the current spot price in domestic currency of one unit of the foreign currency, and that F_0 is the futures price in domestic currency of one unit of foreign currency. This is in line with our previous notation, but does not, however, necessarily correspond to the way spot and future exchange rates are quoted. T and r remain unchanged, and we define r_f as the value of the foreign risk-free interest when money is invested for time T . That leads to equation (9).

$$(9) \quad F_0 = S_0 e^{(r-r_f)T}$$

Equation (9) is also known as the *interest rate parity relationship* and it derives from international finance. It shows that when the foreign interest rate is greater than the

domestic ($r_f > r$), F_0 is always less than S_0 , and F_0 further decreases as time to maturity, T , increases. Similarly, when the domestic interest rate exceeds the foreign interest rate ($r > r_f$), F_0 is always greater than S_0 , and F_0 further increases as T increases. It's also essential to note that equation (8) is equal to equation (9) with q replaced by r_f . This is by no means coincidence, as foreign currency can be regarded as an asset paying a known yield. The yield is the risk-free interest rate in the foreign currency. (Sharpe et al. 1999: 767–771; Bodie et al. 2002: 675–676; Hull 2003: 55–58; Sutcliffe 2006: 141.)

2.2. Futures Trading Strategies

The wide spectrum of derivative instruments has unsurprisingly resulted in an equally extensive amount of different types of traders, and moreover, in a vast number of trading strategies. The main reason why derivative markets have grown outstandingly and attracted so many traders is that they possess a great deal of liquidity. If investor wants to take a certain position and covers one side of the contract, there is no problem in finding another investor willing to take an opposite position, covering the other side of the contract. (Bodie et al. 2002: 750; Hull 2003: 10.)

The great number of traders can be divided into three broad categories: *hedgers*, *speculators* and *arbitrageurs*. Hedgers use derivative instruments to reduce market exposure in order to diminish the risk they face from undesired future market movements. Speculators use them to bet on anticipated price movements of market variables. Arbitrageurs try to take offsetting positions in two or more instruments in the hope of locking in profit. Futures are widely used in hedging and speculating but their use in arbitraging is rather marginal. Therefore, the use of futures in an arbitraging purpose is not examined further in this thesis, but more focus is directed to the use of futures in hedging and speculating, respectively. Furthermore, we will treat futures contracts as forward contracts as we did before, thus ignoring the daily settlement. (Bodie et al. 2002: 750–752; Hull 2003: 10–14; Sutcliffe 2006: 253.)

2.2.1. The Basis and Basis Risk

Before continuing with a further analysis of futures trading strategies, it is important to know and understand the term *basis*. For futures, basis can be defined as follows:

$$\text{Basis} = \text{Spot price of the underlying asset} - \text{Current price of a futures contract}$$

This is the usual definition of basis. However, an alternative, reverse definition, $\text{basis} = F_0 - S_0$, is sometimes used. This thesis consistently defines basis with the first definition. (Sharpe et al. 1999: 664, Bodie et al. 2002: 752; Hull 2003: 75; Sutcliffe 2006: 149.)

The basis can be positive or negative ($S_0 > F_0$ or $S_0 < F_0$) prior to its maturity. However, because of the convergence theory of futures and spot prices ($F_T = S_T$), at maturity basis is zero. In consequence, basis tends to decrease when the delivery approaches, irrespective of whether it is positive or negative. This is illustrated in Figure 3. (Sharpe et al. 1999: 664, Bodie et al. 2002: 752; Hull 2003: 75; Sutcliffe 2006: 152–154.)

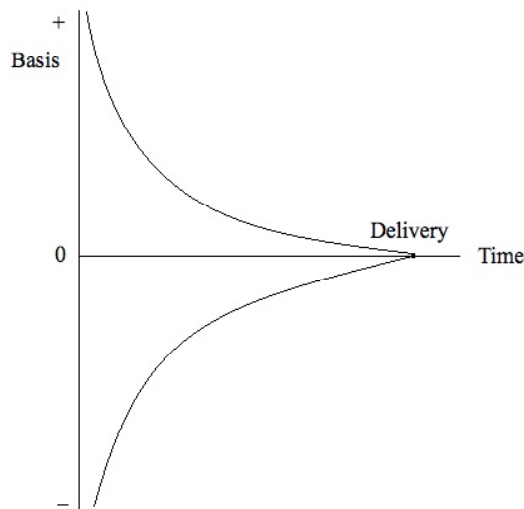


Figure 3. Convergence of the basis.

Even though the basis is certain to be zero at maturity, it can vary significantly prior to that, because the futures price and the spot price need not to move in perfect correlation during the life of the contract. The relative fluctuation between the futures price and the spot price that lead to numerical variations of the basis is known as *basis risk*. It can have considerable importance for investors. To examine basis risk further, the following notation is adopted: F_1 and S_1 are the futures price and the spot price at time t_1 , and similarly, F_2 and S_2 are the futures price and the spot price at time t_2 . We introduce b_1 and b_2 as the basis at time t_1 and t_2 , respectively. From the definition of the basis, we have

$$(10) \quad b_1 = S_1 - F_1$$

and

$$(11) \quad b_2 = S_2 - F_2$$

If we now consider that an investor wants to take a futures position at time t_1 wishing to close it at time t_2 , the risk and uncertainty is b_2 , as it is not known at time t_1 . The term b_2 represents the basis risk. (Sharpe et al. 1999: 664, Bodie et al. 2002: 752–53; Hull 2003: 75–76; Sutcliffe 2006: 154.)

Basis risk tends to be greater for consumption assets than for investment assets. This is because the arbitrage arguments lead to a well-defined relationship between the futures price and the spot price for an investment asset, and the basis risk mainly arises from uncertainty as to the level of the risk-free interest rate in the future. For consumption assets, however, the imbalances between supply and demand as well as storing difficulties can result in large variations in the convenience yield, which in turn leads to increase in the basis risk. It should also be noted that as the basis converges to zero as delivery approaches, it is plausible to expect that the basis risk will also drop down to zero at maturity, as shown in Figure 4. (Hull 2003: 76–77; Sutcliffe: 154–155.)

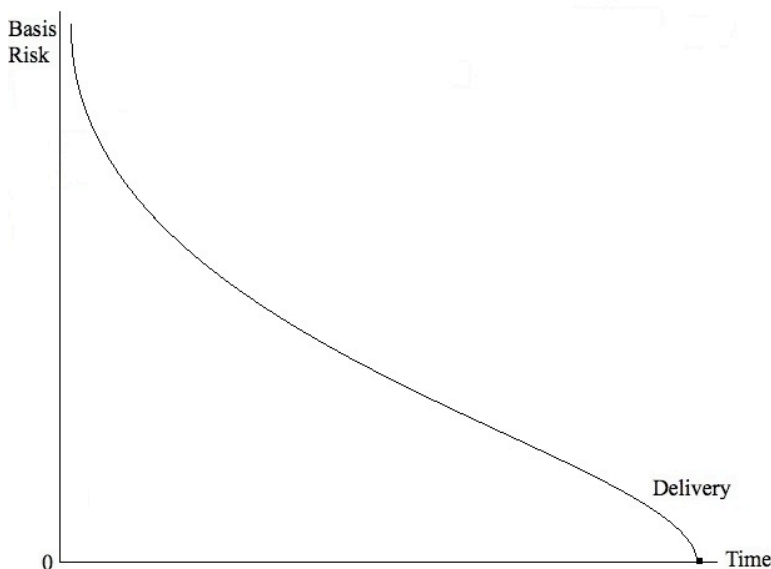


Figure 4. Convergence of basis risk.

2.2.2. Hedging

The majority of futures markets participants are hedgers. Their aim is to use futures markets to reduce a risk they face. For example if a company knows they need a certain amount of gasoline at a certain time in the future, but are afraid the price of oil will rise before that, they can take a long position in oil futures and lock the price in advance. Then, if the price of oil does rise they can just accept the delivery. If the price of oil stays the same or drops, they can close out the contract prior to delivery. Every hedger pursues the *perfect hedge* that eliminates the risk completely. The perfect hedge, however, is only theoretical and if not impossible, very rare at least. Therefore, it is much more practical to examine hedging from a point in which hedges are constructed to provide the best cover possible for a certain hedging objective. (Sharpe et al. 1999: 654–655; Bodie et al. 2002: 750-753; Hull 2003: 70–75; Sutcliffe 2006: 253-258.)

Many times hedging is not as straightforward as in the example above. The reasons for that are as follows.

1. The asset being hedged may not be exactly the same as the asset underlying the futures contract.
2. The hedger may be uncertain as to the exact date when the asset will be bought or sold.
3. The hedge may require the futures to be closed out well before its expiration date.

These problems constitute basis risk. We already know that basis risk should be zero at maturity, if the asset hedged is the same as the asset underlying the contract. If this is not the case, the basis risk is usually greater. Another important factor affecting basis risk is the choice of the delivery month. The range of delivery months does not necessarily correspond exactly with the expiration of the hedge. In this case the usual policy is to choose the closest possible delivery month which is nevertheless later than the hedge expiry. Thus, for example, a long hedger avoids the risk of having to accept delivery. In general, basis risk increases as the interval between the hedge expiration and the delivery month increases. It's also essential to note that the basis risk can lead to an improvement or a worsening of a hedger's position. If the hedge is short, an unexpectedly strengthening basis improves the hedger's position and an unexpectedly

weakening basis worsens it. For a long hedge, the reverse is true. (Hull 2003: 75–7; Sutcliffe: 253–258.)

The ratio of the size of the position taken in futures contracts to the size of the exposure is called the *hedge ratio*. As the objective for a hedger is to minimize risk, a hedge ratio equal to 1.0 is not necessarily optimal. The *optimal hedge ratio*, h^* , is the product of the coefficient of correlation between the changes in spot price and futures price, and the ratio of the standard deviation of the changes in the spot price to the standard deviation of the changes in futures price. If we indicate the changes in the spot price and the changes in the futures price with δS and δF , and the standard deviations of δS and δF with σ_S and σ_F , we have

$$(12) \quad h^* = \rho\sigma_S/\sigma_F$$

The optimal hedge ratio is the slope of the best-fit line when δS is regressed against δF . This is reasonable, as we require h^* to correspond to the ratio of changes in δS to changes in δF . This is illustrated in Figure 5. (Hull 2003: 78–80; Sutcliffe 2006: 258–261.)

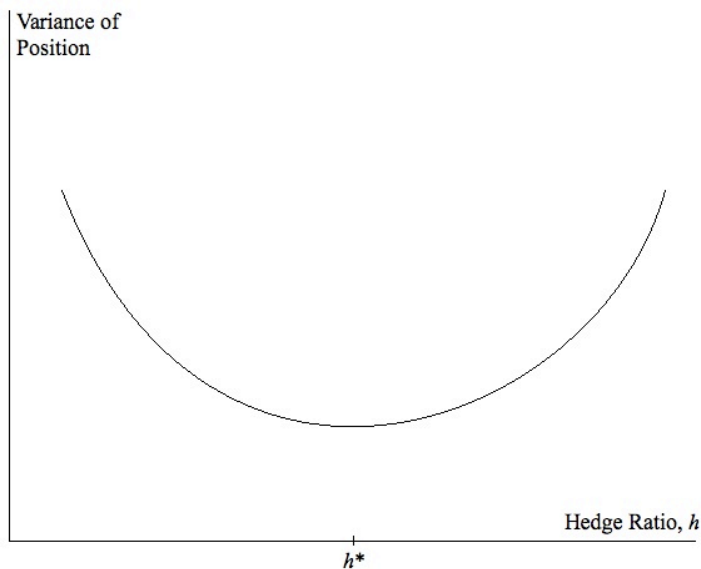


Figure 5. Dependence of variance of position on hedge ratio.

Optimal hedge ratio, h^* , is needed when calculating the optimal number of contracts to hedge a position. If we notate the size of the position being hedged in units as N_A , and

the size of one futures contract in units as Q_F , we can write the optimal number of futures contracts for hedging, N^* , as follows:

$$(13) \quad N^* = h^*N_A/Q_F$$

From equation (13) we can derive the formula on how to hedge equity portfolios with stock index futures. If the portfolio mirrors the index precisely, the hedge ratio of 1.0 is clearly appropriate, and we can solve the number of futures contracts that should be shorted from equation (14), with P being the current value of the portfolio and A being the current value of the stocks underlying one futures contract.

$$(14) \quad N^* = P/A$$

But if the portfolio does not exactly mirror the index, which is often the case, the parameter beta, β , from the capital asset pricing model³ can be adopted to determine the suitable hedge ratio. Beta is the slope of the best-fit line obtained when excess return on the portfolio over the risk-free rate is regressed against the excess return of the market over the risk-free rate. Assuming that the index underlying the futures represents the schema of the market, it can be shown that the suitable hedge ratio is the beta of the portfolio. This means we can extend equation (14) to

$$(15) \quad N^* = \beta P/A$$

This formula ignores the daily settlement and assumes that maturity of the futures contract is close to expiry of the hedge. With this model, futures can be used to change the beta of a portfolio to something other than zero. In general, an investor can change the beta of a portfolio from β to β^* , when $\beta > \beta^*$, with a short position of

$$(16) \quad (\beta - \beta^*)P/A$$

futures contracts. Similarly, when $\beta < \beta^*$, a long position in

$$(17) \quad (\beta^* - \beta)P/A$$

³ Capital Asset Pricing Model (CAPM) by Harry Markowitz will not be further explained in this thesis. For further information see e.g. Lintner (1965), Black, Fischer, Jensen and Scholes (1972) and Mullins (1982).

futures contracts are required. (Hull 2003: 78–85; Sutcliffe 2006: 261–271.)

2.2.3. Speculating

Speculators are already by definition very different from hedgers. When examining the speculating as trading strategy, the disparity widens even further. Unlike hedgers, speculators' sole purpose is to make a profit by forming an opinion about the future progress of the market and then taking a position accordingly. If the market behaves according to their view, they gain profits, if not, they make a loss. In other words, they bet on the direction of the markets. Speculation with derivatives is considered to be very risky and very significant losses are possible (Sharpe et al. 1999: 654–655; Bodie et al. 2002: 750-752; Hull 2003: 10-13.)

In the futures markets the speculators bet on the future price movements of the underlying asset, and thus, on the price movements of the futures as well. If the investor believes the prices will rise, he or she takes a long position in certain futures. If the prices do rise, the value of the investor's long position escalates. Like shown in the equation (1), the payoff from a long position, $S_T - K$, can be theoretically infinite, as S_T can grow to infinity. In reality, this does not of course happen, but the gains from a long position can be significant. The loss from long position, however, is limited to K , because S_T cannot be negative. Although the loss of long position is limited, it can still be very significant. (Bodie et al. 2002: 750-752; Hull 2003: 10-13.)

Moreover, if an investor predicts that prices will fall, he or she is certain to take a short position. This way, if the prices do fall, the investor makes the profit in equation (2), $K - S_T$. Opposite to long position, the loss from a short position can be infinite, as S_T can again rise to infinity. Similarly, the gain from a short futures position is limited to K . The payoffs from long and short futures positions are illustrated in Figure 3. (Bodie et al. 2002: 750-752; Hull 2003: 10-13.)

When speculating, the futures contracts hardly ever lead to delivery. If the price movements are favourable to the investor, he or she is likely to close out the contract prior to maturity to lock in profits. If the investor thinks the price movements will continue to be favourable, and wants to maintain the position, he or she can *roll the position forward* by closing out the contracts and buying the same contract with the next delivery month. In contrast, if the price movements are unfavourable to the investor,

and he or she does not believe the trend is going to move during the life of the contract, the investor is likely to close out the contract to avoid further losses. In reality, if the position is large or highly unfavourable against the price movements, the marking to market function requires great liquidity to stay in the position, as investor has to provide the daily variation margins, which in futures speculation can be very significant. (Sharpe et al. 1999: 654–655; Bodie et al. 2002: 750-752; Hull 2003: 10-13.)

Due to the very risky nature of an outright futures position, many speculators use *spreads*. Spread trading basically means that the investor simultaneously takes long and short positions with many different assets and with various delivery months. The idea is that even though some contracts result in losses, others will provide profits, thus providing cover. Of course the aim is to gain wins, but the exposure with spreads is less risky. There is a wide selection of different spread strategies to choose from, ranging from a *intracommodity spread* to a *calendar spread*. (Sutcliffe 2006: 183–192.)

There are two major reasons why speculators want to use futures instead of the actual underlying assets. First, the transaction costs, which are far greater when trading assets and not futures. Second, the *leverage* that can be obtained by speculating with futures is better than with assets. If an investor wants to take a large position with assets, he or she is required to up-front a large investment. The same position with futures requires only the initial margin, which usually is about 10% of the positions' value. The possible gains, however, are equal. Therefore, futures allow investors to achieve much greater leverage than would be available from directly trading the assets. (Sharpe et al. 1999: 654–655; Bodie et al. 2002: 750-752; Hull 2003: 10-13.)

2.3. Futures Prices and Expected Spot Prices

One of the oldest controversies in theory of futures concerns the relationship between the futures price and the expected spot price. From very early on there has been the expectation that futures prices are normally below the expected spot prices. This theory was first proposed by Keynes (1930) and Hicks (1946), who argued that, as hedgers tend to short the futures markets to protect their investments, they simultaneously pay the speculators a *risk premium* to offset their risk, and to take corresponding long positions, thus causing futures prices to rise during their life because they converge with spot price at maturity. Furthermore, speculators would not take long positions if there

were not an expectation of a profit from holding the futures contract, which results as a positive risk premium. This theory is called the *normal backwardation*. It is in line with the view that hedgers as a group take short futures positions while speculators collectively adopt long positions. (Bodie et al. 2002: 758–760; Hull 2003: 31–63; Sutcliffe 2006: 192–198.)

Another theory on the behaviour of the futures prices in contrast with the expected spot prices, also recognized by Keynes and Hicks, is the reverse theory of normal backwardation, where the hedgers would be net long and speculators would take short positions. Then the futures price would lie above the expected spot price, resulting in a negative risk premium, and the price of a futures contract would fall during its life, earning gains for those who are short. This theory is known as the *contango*. (Bodie et al. 2002: 758–760; Hull: 13–63; Sutcliffe: 192–198.)

If we use our previous notation with implementation of $E(S_T)$ as the expected spot price, we can write the normal backwardation as

$$(18) \quad F_0 < E(S_T)$$

and the contango as

$$(19) \quad F_0 > E(S_T)$$

In the case of normal backwardation the risk premium is positive, $E(S_T) - F_0$, and thus futures prices will rise during their life. When contango applies, risk premium is negative, $F_0 - E(S_T)$, and futures prices will fall during the life of the contract. The situation where $F_0 = E(S_T)$ is in some literature called the *expectation hypothesis*. It is, however, only a theoretical and somewhat naive hypothesis, which relies on the notion of risk neutrality, explicating that if all market participants are risk neutral, they should agree on a futures price that provides an expected return of zero to all parties. The normal backwardation, contango, and the expectation hypothesis are illustrated in Figure 6. (Bodie et al. 2002: 758–760; Hull: 13–63; Sutcliffe: 192–198.)

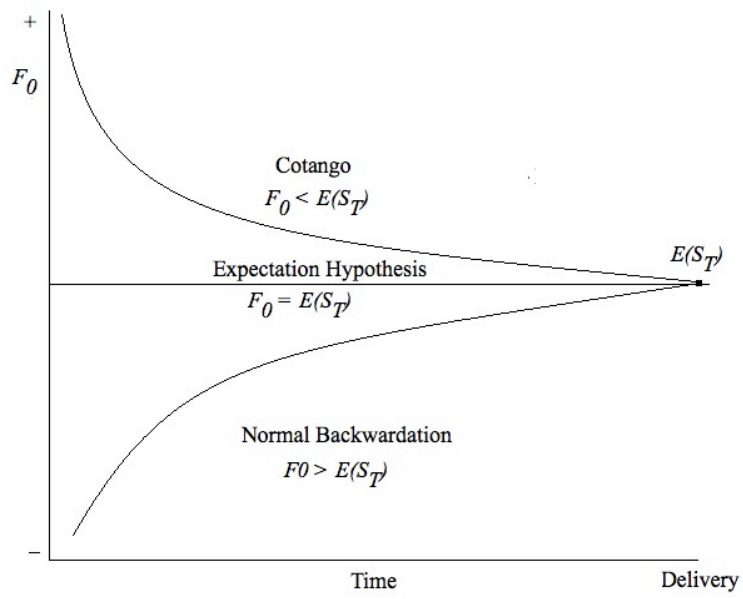


Figure 6. Different patterns of futures prices.

3. STOCK INDEX FUTURES

Since their introduction back in 1982, stock index futures have been extremely popular and widely used financial instruments around the world. The growth of trading in stock index futures in the USA and Japan has been even more dramatic than in Europe. Especially their ability to provide a comprehensive hedge for equity portfolios with rather low costs makes stock index futures appealing to investors. Other reasons for their popularity include good leverage, very liquid market and also taxation and regulation aspects, thus making stock index futures important tools for speculating causes as well. (Bodie et al. 2002: 773–776; Sutcliffe 2006: 3–19.)

The implementation of cash settlement in the late 1970s was with no doubt the most influential factor in the origination of stock index futures. It is an essential practice in all financial futures and particularly in stock index futures. Without it, having to be settled with the traditional delivery, stock index futures would be clumsy and impractical investment tools. Their delivery would require trading in hundreds of different stocks. Despite the rather straightforward prestige of stock index futures, they are, contrary to common belief, highly versatile and diverse. This chapter will further focus on those attributes of stock index futures, and on the prospects and risk they pose. (Bodie et al. 2002: 773–776; Sutcliffe 2006: 3–19.)

3.1. Introduction to Stock Indexes

A stock index is a method of measuring a section of the stock market. It can consist of different number of stocks chosen on various grounds and can be classified in many ways. The development of stock market indexes arises from the growing demand to measure widespread movements of the stock markets, as opposed to just monitoring the price movements of individual stocks. Stock market indexes' ability to provide historical comparison on returns on money invested in the stock market against investment in some other assets, and their status as the leading indicators of national economic performance, has established stock indexes as the barometers for the health and change of the financial markets. (Investopedia 2009; Sutcliffe 2006: 3–4.)

The first ever stock index was composed in New York by Charles Dow in 1884, and at first it consisted of stocks of 20 companies, most of them in the railroad industry. In 1896 the index was named DJIA. Amazingly, this index still exists and is naturally the oldest still quoted index in the world. Since its inception over a hundred years ago, endless numbers of indexes have followed. (Kuznetsov 2006: 180; Sutcliffe 2006: 3–4.)

3.1.1. Properties of Stock Indexes

There are two main differences between stock indexes, the first being the sector of the market the index measures. A *broad base* index represents the performance of a whole stock market by comprising stocks from a great number of large companies operating in various sectors market-wide. These indexes are usually the most regularly quoted as they are listed in nations' major exchanges, including DJIA in NYSE, NASDAQ-100 in NASDAQ, S&P 500 in NYSE and NASDAQ, FTSE 100 in London Stock Exchange (LSE), DAX 30 in Frankfurt Stock Exchange (FWB), CAC 40 in Euronext Paris and Nikkei 225 in Tokyo Stock Exchange (TSE). (Investopedia 2009; Natenberg 1994: 301; Sutcliffe 2006: 3–4.)

But there are also indexes monitoring smaller and more particular segments of the market. These indexes can consist of shares from companies in a certain sector, a certain size or market value, with a certain type of management, or more recently, companies with only ethnically approved products or companies with similar environmental values. The latter two are, however, often criticized of giving a partially subjective outcome. (Natenberg 1994: 301; Sutcliffe 2006: 3–4.)

Stock indexes can encounter problems and have sometimes been criticized of being misleading. The companies chosen for the indexes are usually above-average performers, which tends to bias the indexes. There are also concerns regarding the procedure of removing shares from the index. Furthermore, some published values of stock market indexes are, in fact, averages of a number of values of the index compounded at different times. This averaging can considerably alter the portfolios in the efficient set. In addition, nonsynchronous trading also leads to the values of indexes being averages, as prices used to compose the index do not occur at the same moment. Nonsynchronous trading means that as some shares in the index are not traded as continuously as others, their prices are not current, but rather averages of a certain time period. There are also numerous problems related to the valuing methods of the indexes,

which are further discussed in the next chapter. (Natenberg 1994: 301; Sutcliffe 2006: 15–17.)

3.1.2. Calculating the Value for a Stock Index

Another notable difference between stock indexes is the calculation method on which their value is based. Indexes can be classified by the criteria they use: the weighting system and the averaging procedure. All the valuing methods have advantages and disadvantages. The simplest way to construct an index is to use the share prices directly without applying any weights. Thus, movements in the share price of companies with higher share price are likely to be dominant to movements in the share prices of companies with lower share price, as they will tend to move in larger absolute amounts. Indexes valued like this, for example the DJIA, are called *price-weighted* indexes. Another way of establishing a value for an index is to use the *equal weight* method. It gives each share in the index an equal weight by considering the proportionate change in their price. Although an equally weighted index, unlike a price-weighted index, avoids the distortion of companies with high share price skewing the value of the index, it doesn't, however, take into consideration the size of the companies, and thus gives the same importance to share prices of companies with very different market capitalizations. (Natenberg 1994: 302–305; Sutcliffe 2006: 4–5.)

In contrast to the two previous weighting methods is the *market-value-weighted* index, or better known as the *capitalization-weighted* index. The adoption of this weighting method has the considerable advantage that each share is weighted in accordance with its importance in the average portfolio of shares, making it significantly harder to manipulate than most other weighting schemes. The problem a capitalization-weighted index can face is that some of the companies in the index have substantially large weights, accounting for a very significant proportion of the entire index value, thus being able to dominate the index. This is usually prevented by setting up upper bounds, caps, on the weight a single company can be given. Recently, major index providers have switched to using free-floating weights for the capitalization-weighted indexes. The free float is the market value of shares in the company available for trading, thus being a more realistic measure of a tradable portfolio. Many of the major stock indexes are capitalization-weighted, including the S&P 500. (Natenberg 1994: 302–305; Sutcliffe 2006: 4–5.)

Regardless of the weighting method used for the index, the prices of individual shares must be aggregated to produce a single number, the value of the index. This is done with one of two ways: the *arithmetic average* (AW) or the *geometric average* (GW). If we consider $x_1, x_2, x_3 \dots x_n$ to be the prices of the shares in the index and $w_1, w_2, w_3 \dots w_n$ to be the weights of the corresponding companies, we can write AW as follows.

$$(20) \quad AW = (w_1x_1 + w_2x_2 + w_3x_3 + \dots w_nx_n)$$

The value of n is the number of companies represented in the index. Furthermore, using the same notation we get

$$(21) \quad GW = (x_1^{w_1})(x_2^{w_2})(x_3^{w_3}) \dots (x_n^{w_n})$$

The geometric average is thought to have two advantages when compared to the arithmetic average. First, when the base data of a share has to be changed or the share entirely substituted with another, it is easier to do this with a geometric index than an arithmetic index. Second, a geometric index is proven to be superior to a arithmetic index in all of the desirable features of a stock index when information asymmetry is in place (Lien and Luo 1993). However, when the shares in the index have normally distributed returns or if one or more of the share prices collapses close to zero, the arithmetic index is thought to be more appropriate. It is also suggested that a geometric index undervalues price rises to price falls, whereas a arithmetic index gives more accurate values. The arithmetic average is clearly more popular than the geometric index when it comes to stock indexes. Both S&P 500 and DJIA are calculated with an arithmetic average. (Wilmott et al. 1996: 223–226; Sutcliffe 2006: 6–12.)

3.2. Qualities for Stock Index Futures

Stock index futures differ from other futures in some ways. The cash settlement is the most significant difference to traditional commodity futures, which underlie consumption assets. But stock index futures also have attributes and qualities that other financial futures lack. For example, the price discovery, the way information flows first to the futures market instead of the spot market, is more sensitive in stock index futures because the market for them is so liquid. There have been studies that suggest that the introduction of a market for index futures causes the shares' prices to be more

informative (e.g. Green 1986), and studies that at the same time argue that the share prices are, in fact, less informative (e.g. Covey and Bessler 1995). Ultimately, the effect of the introduction of index futures on the price discovery of share prices is an empirical matter. (Sutcliffe 2006: 158–162.)

Also, spread trading with stock index futures is somewhat more appealing than with other futures. This is mainly due to the very large supply of different index futures, but also to the fact that the correlation, whether positive or negative, can in many cases be considered more obvious between stock indexes than for example between currencies. Furthermore, empirical studies have shown that spread traders, whether trading intracommodity spreads or intercommodity spreads, can come across highly favourable *spread ratios* when trading in stock index futures (Yadav and Pope 1992). (Sutcliffe 2006: 183–192.)

Despite some restricting factors, stock index futures are very popular among fund managers. They are often used to reduce stock market exposure and provide cover from unfavourable price changes, whereas forwards are mainly used to provide cover from undesired changes in currency rates. Most of the fund managers utilising index futures, base the use on two qualities of stock index futures: the ability to control the beta of the portfolio, and the ability to vary the size of the investment in the market. If the fund manager tries to change the beta of the portfolio by just trading shares, efficiency will be lost. Also, varying the size of the investment by just trading shares is more difficult and costly than trading index futures. There are a number of ways how fund managers can use index futures based on these two properties: changing and rebalancing the asset allocation, reducing exchange risk for foreign investors, insuring portfolios and delaying taxation, to name a few. (Sutcliffe 2006: 301–330.)

The lead-lag relationship between the stock market and the futures market has also been noticed to be slightly more sensitive than with other futures, mainly due to the very high liquidity of the stock index futures markets. The lead-lag basically means that the futures prices precede the prices of the underlying spot, or vice versa. This lead-lag relationship will be further discussed and examined in the upcoming parts of this thesis. (Sutcliffe 2006: 162–163.)

4. DATA AND METHODOLOGY

The relationship between stock index futures and their underlying stock indexes is a widely studied research area. It has been investigated on many different markets worldwide and with an array of various research methods. Some of these are reported in chapter 1.

This thesis focuses on the United States stock and futures markets. They are the largest in the world in both total value of trading and liquidity (WFE 2009). The relationship between these two markets is studied with Granger causality theorem and vector error correction model (VECM), which is formed by adding an error correcting feature (such as a residual) to a VAR model (Engle & Granger 1987). These methods and the data will be further discussed in this chapter.

4.1. Data Description

This study examines the lead-lag relationship of two major stock indexes, S&P 500 and DJIA, and the futures written on them, SP and DJ. S&P 500 and DJIA are respectively the number one and number two most followed indexes of large-cap American stocks. They both consist of actively traded and widely held stocks of large, blue-chip companies. DJIA includes the stocks of 30 companies and S&P 500 represents the stocks of 500 companies. S&P 500 is a capitalization-weighted index, whereas DJIA is a price-weighted index. Both the indexes are calculated with arithmetic averages. A detailed explanation of the valuation of stock indexes can be found in chapter 3. (S&P 500 2009; DJIA 2009; Sutcliffe 2006: 11-12.)

All the shares in the two indexes trade in one of the two major American stock exchanges, NYSE or NASDAQ. According to the World Federation of Exchanges (WFE), NYSE and NASDAQ are the two largest exchanges in the world. Out of the 53 major stock exchanges around the world, NYSE and NASDAQ shared a total value of trading in excess of 70 billion USD in 2008, while the remaining exchanges totalled only around 43 billion USD combined. (WFE 2009.)

Futures underlying the two indexes are SP and DJ. They are both traded in the CME and are very liquid with large open interests. The SP has a contract size of 250 (times the index) and the DJ has a contract size of 10. Both of the futures are on a so-called March quarterly cycle, meaning that they expire every three months from March (June, September, December and again March). Furthermore, the last trading day for SP is the third Friday of the expiration month, and for the DJ it is the Thursday before that. The minimum tick change for SP is 0,01 index points, whereas the minimum tick change for DJ is 1 index point. (CME 2009.)

The CME is the largest derivatives exchange in the world. It gained significantly more trading activity when it merged with CBOT in 2007 and with New York Mercantile Exchange (NYMEX) in 2008. After the mergers the corporation became officially known as CME Group. (CME 2009.)

The data in this thesis is intraday data running from August 1, 2008 to March 19, 2009. The last price of every 5-minute interval from the two indexes and from the two futures is obtained. As NYSE and NASDAQ are open for trading from 9.30 a.m. to 4 p.m. ET every business day, that time period is when S&P 500 and DJIA have changing values. The CME is open for outcry trading from 9.30 a.m. to 4.15 p.m. ET. It also has an electronic trading platform called Globex which is open for trading almost 24 hours a day.

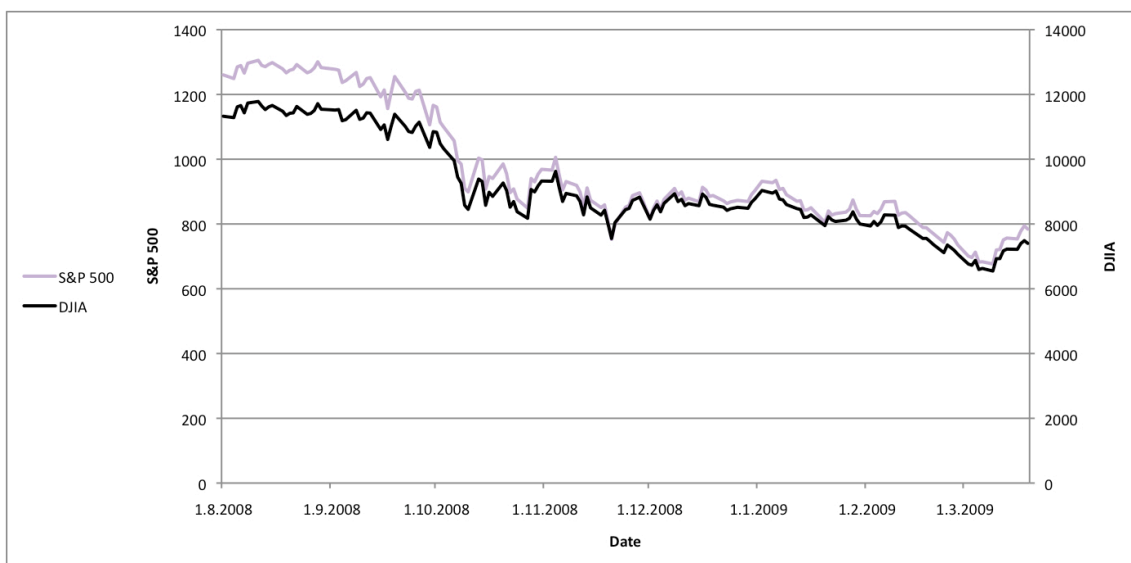


Figure 7. Movement of the S&P 500 index and the DJIA index during the data period.

As there is a risk that the nonsynchronous trading hours can bias the data and thus result in an incorrect empirical analysis (Chang 1992), this thesis obtains the futures prices only from the time period that the indexes have changing values, i.e. from 9.30 a.m. to 4 p.m. ET every business day. The movement of the two indexes during the data period is illustrated in Figure 7. It clearly shows the data period colliding with the global financial recession, as both indexes drop significantly. (NYSE 2009; NASDAQ 2009; CME 2009.)

The futures prices obtained are always from the futures contract closest to maturity. As the futures contract's trading volume only activates from three to four months before maturity and significantly intensifies when maturity is approaching, the most informative prices are collected from the contracts closest to expiration (Subrahmanyam 1991). After the last trading day the futures prices are obtained from the next futures contract up for expiration. All data mentioned above is gathered from Bloomberg.

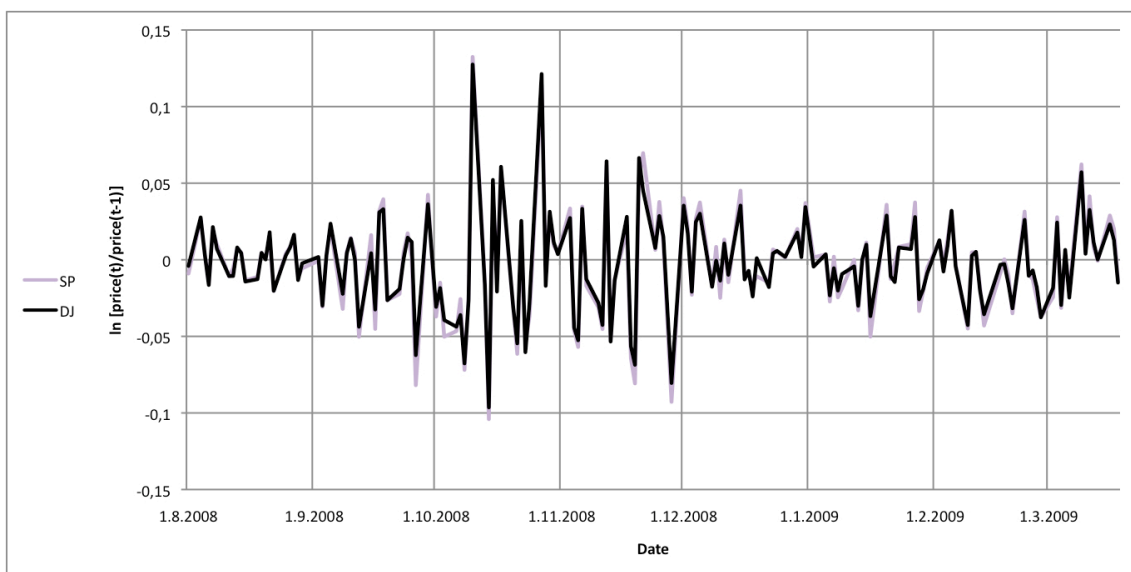


Figure 8. The fluctuation of returns for SP and DJ during the data period.

It should be mentioned that in this study the lead-lag relationship between futures markets and stock index markets is investigated using futures returns and stock index returns, instead of the flat prices (levels). The returns time series can be formed from the price time series by collecting the change between price t and price $t + 1$. It is also necessary to transform the return time series to a logarithmic form. This is because as the number of levels increases, the change usually also increases, making the return

values irrelative to one another. By transforming the time series *logarithmic*, we can guarantee all the values to be relative. Statistically, the return time series are formed as follows.

$$(22) \quad \Delta y = \ln (y_t/y_{t-1})$$

where y is the price and Δy is the return. The returns' fluctuation during the data period for the two futures is presented in Figure 8.

4.2. Methodology

The next chapter focuses on the research methodology used in this thesis. Some important concepts and relevant statistical procedures in time series analysis are presented. The objective for this chapter is to lay groundwork for the empirical analysis conducted in the next part of the thesis.

4.2.1. Stationarity, White Noise and Unit Root

It is common for economic time series not to converge to any long-run equilibrium. Especially for financial time series with stochastic process x_t , it is usual that distribution function x_{t+j} is dependent on t . This means that the variance of x_t will go to infinity as time goes to infinity. Such time series are said to be *non-stationary*. Furthermore, when creating models for time series, it is necessary to know whether the stochastic process is time-dependent or not. If the stochastic process is in fact dependent on time, i.e. the time series is non-stationary, the stochastic process changes over time making it difficult to find an accurate model for it. Any found models for non-stationary time series, although suggesting causality between the variables, are biased. The results from the regression may be due to strong trends or correlation, and are not the sign of actual causality. (Granger and Newbold 1986: 3-4.)

Generally, empiric time series analysis is based on a *stationary* process. The differences between non-stationary and stationary time series are crucial, and distinguishing between the two properties is often a precondition for statistical inference. The statistical definition of stationarity is that the joint distribution of x_t and x_{t-j} depends

solely on j and not on t . Further, a stochastic process is said to be stationary if its mean and autocovariances are unaffected by a change of time origin. Formally a stochastic process with a finite mean and variance is stationary when the following conditions apply for all t and $t-s$:

1. $E(y_t) = E(y_{t-s}) = \mu$
2. $E[(y_t - \mu)^2] = E[(y_{t-s} - \mu)^2] = \sigma_y^2 < \infty$
3. $E[(y_t - \mu)(y_{t-s} - \mu)]E[(y_{t-j} - \mu)(y_{t-j-s} - \mu)] = \gamma_s$

where μ , σ_y^2 and γ_s are all constant. The first condition ensures that a time series has no trend. The second condition states that a time series has a time-independent and finite variance. Finally, the third condition concludes that the covariance of observations depends only on $t-s$, and not on point of time t . (Granger and Newbold 1986: 3-6.)

A concept closely related to stationarity is *white noise*. A sequence that does not exhibit any relationship between its past, present and future realisations is called white noise, ε_t . Sequence ε_t is said to be a white noise process if each value in the sequence has a mean of zero, a constant variance, and is distributed independently of all other values in the sequence. Formally ε_t is a white noise process if following conditions apply for every t :

1. $E(\varepsilon_t) = E(\varepsilon_{t-1}) = 0$
2. $E(\varepsilon_t)^2 = E(\varepsilon_{t-1})^2 = \sigma^2$
3. $Cov(\varepsilon_t, \varepsilon_{t-s}) = Cov(\varepsilon_{t-j}, \varepsilon_{t-j-s}) = 0$

where $s \neq 0$. (Granger and Newbold 1986: 312-313.)

Furthermore, a non-stationary time series can be modulated to a stationary time series by the method of differentiation. The number of times a non-stationary time series has to be differentiated to become stationary depends on the time series' *order of integration*. Order of integration is notated $I(d)$. Moreover, a time series that is $I(d)$ is said to have d *unit roots*. Thus, a time series that is $I(d)$ has to be differentiated d times to become stationary, i.e. not to have a unit root. Therefore, a time series is stationary when it is $I(0)$. (Granger and Newbold 1986: 262-263.)

Like mentioned earlier, it is fairly common for economic time series to have a unit root. It is, however, rare that the number of unit roots exceeds one. If a time series is $I(1)$, it means that the change is stationary. This process has importance in asset pricing as $I(1)$ time series depicts the random walk properties of asset prices, which is fundamental in efficient market hypothesis. A stochastic process is integrated of order 1 when

$$(23) \quad y_t = \mu + y_{t-1} + \varepsilon_t$$

where ε_t is white noise and μ is a constant drift term. From (23) we can further derive a regression model representing a process integrated of order 1:

$$(24) \quad y_t = \mu + \rho y_{t-1} + \varepsilon_t$$

when $\rho = 1$. (24) is a first order autoregressive model (AR(1)) with a constant drift term. Dickey and Fuller (1979) showed that with (24) it is possible to test whether y_t has a unit root. The test is called the Dickey-Fuller test. If we consider $\gamma = \rho - 1$, we get a null hypothesis $\gamma = 0$. If this null hypothesis is approved, y_t is integrated of order 1, thus being non-stationary. (Granger and Newbold 1986: 262-263.)

The Dickey-Fuller test assumes the error term to be white noise. When estimating regression model (24), a standard t-statistic can be computed for the estimate of ρ . However, the estimate of ρ does not have a limiting normal distribution and the t-statistic is not t-distributed. (Dickey and Fuller 1979.)

A more dynamic test for unit roots is the augmented Dickey-Fuller (ADF)-test. It was derived from the standard Dickey-Fuller test by Dickey and Said (1984). It is more congenial for larger and more complicated set of time series models. The ADF-test computes the same testing procedure as the standard Dickey-Fuller test, applying it to the following model (Granger and Newbold 1986: 262-263.):

$$(25) \quad y_t = \mu_0 + \gamma y_{t-1} + \sum_{i=1}^p \beta_i \Delta y_{t-i} + \varepsilon_t$$

where

y_t = the sequence investigated for a unit root;

μ_0 = drift term;

γ = the parameter of interest;

p = number of lags;

ε_t = white noise.

The null hypothesis tested is $\gamma = 0$. If the ADF-test can't reject the null hypothesis, sequence y_t contains a unit root. The test involves estimating (25) using Ordinary Least Squares (OLS) in obtaining the estimated value for γ and the associated standard error. The resulting t-statistic is compared with the critical values provided by McKinnon (1991), as the critical values by Dickey and Fuller (1979) are proven to be inadequate. From the comparison the null hypothesis can be either accepted or rejected. The number of lags can be determined by using information criterion methods such as Akaike's Information Criterion (AIC) (Akaike 1974). Finally, it should be mentioned that all statistical tests for unit roots are somewhat robust and the existence of unit root can rarely be entirely ruled out. (Granger and Newbold 1986: 262-264.)

4.2.2. Co-integration

Two time series can be linked in a way where they form a long-run equilibrium moving closely together over time and the difference between them will remain stable. Time series having this quality are said to be *co-integrated*. In statistical terms, if two time series x_t and y_t that are both $I(d)$, form an equation

$$(26) \quad z_t = x_t - \alpha y_t$$

so that there exists a constant vector $\alpha (\neq 0)$ such that $z_t \sim I(d-b)$, $b > 0$, then x_t and y_t are co-integrated. It is notated $(x_t, y_t) \sim CI(d, b)$. (Granger and Newbold 1986: 224-225.)

The case with greatest practical importance is when $d = b = 1$, meaning that both x_t and y_t are $I(1)$. Generally, it holds that if x_t and y_t are $I(1)$, their linear combination z_t is also $I(1)$. However, when x_t and y_t are co-integrated it is possible that (26) holds. Then $z_t \sim I(0)$, i.e. z_t is stationary. The vector α that reduces order of integration in the system is called a *co-integration vector*. This is a rather special condition, because it means that both series x_t and y_t individually have important long-run components but that in forming their linear combination z_t these long-run components cancel out and vanish. (Granger and Newbold 1986: 224-225.)

Engle and Granger (1987) have proposed a method for testing co-integration. It is based on the ADF-test. First, it needs to be established that the time series tested for co-

integration are integrated of the same order. If two time series are not integrated of the same order, it is obvious they are not co-integrated. Second, the long-run relationship of the time series tested needs to be estimated. This can be done by examining the residual sequence estimated from the following regression model:

$$(27) \quad y_t = \beta_0 + \beta_1 x_t + e_t$$

where e_t is the residual. If the estimate of $e_t \sim I(0)$, i.e. stationary, y_t and x_t are co-integrated. We can further derive the regression for estimating e_t :

$$(28) \quad \Delta \hat{e}_t = \alpha_1 \hat{e}_{t-1} + \varepsilon_t.$$

Now if the ADF-test can not reject the null hypothesis $\alpha = 0$, then the residual sequence contains a unit root. However, if the null hypothesis is rejected, the residual sequence is stationary and thus, time series x_t and y_t are co-integrated. The t-statistic for the estimate of e_t is once again compared to the critical values provided by MacKinnon (1991) in order to decide whether to reject or accept the null hypothesis. The problem of testing co-integration with Engle Granger methodology is that often theory can not suggest which are independent and which are dependent variables. This causes the underlying assumption to be somewhat random, and reversing the order can produce completely different results. (Granger and Newbold 1986: 262-264.)

4.2.3. Granger Causality Theorem

In order to establish a lead-lag relationship between spot and futures markets, the possible causality relations between the two need to be examined. Causality can be tested with a test based on *Granger causality* theorem, introduced by Granger (1969). According to Granger, sequence x_t is said to be Granger-causing sequence y_t , if we are able to better predict the sequence y_t using all available information in x_t , instead of using just the information in lagged values of y_t . In other words, we test whether x_t improves the forecasting performance of y_t . (Granger and Newbold 1986: 259-260.)

Statistically, Granger causality can be determined as follows. If we define y_t by

$$(29) \quad y_t = a_{10} + a_{21}(1)y_{t-1} + a_{21}(2)y_{t-2} + \dots + a_{22}(1)x_{t-1} + a_{22}(2)x_{t-2} + \dots + \varepsilon_{xt}$$

then x_t does not Granger cause y_t if $a_{22}(1) = a_{22}(2) = \dots = 0$. For empirical analysis Granger causality can be tested by estimating the regression models

$$(30) \quad \Delta y_t = \sum_{i=1}^q \alpha_{11}(i) \Delta y_{t-i} + \sum_{i=1}^p \alpha_{12}(i) \Delta x_{t-i} + \varepsilon_{yt}$$

$$(31) \quad \Delta x_t = \sum_{i=1}^q \alpha_{21}(i) \Delta x_{t-i} + \sum_{i=1}^p \alpha_{22}(i) \Delta y_{t-i} + \varepsilon_{xt}$$

where

Δy_t = S&P 500 or DJIA returns;

Δx_t = SP or DJ returns;

ε_{yt} and ε_{xt} are white noise disturbances;

q and p are lag parameters;

$\alpha_{11}, \alpha_{12}, \dots, \alpha_{22}$ are all parameters.

The two null hypotheses tested are $\alpha_{12}(i) = 0$ ($j = 1, \dots, p$) and $\alpha_{22}(i) = 0$ ($j = 1, \dots, p$). F-test⁴ can be employed. When testing the Granger causality theorem there can be four possible outcomes. There can be evidence of one-way causality from y_t to x_t or from x_t to y_t . Furthermore, there can also exist a two-way causality relationship from y_t to x_t and from x_t to y_t , respectively. Finally, if both null hypotheses are accepted, y_t and x_t have no apparent causal relationship. (Granger and Newbold 1986: 259-260.)

4.2.4. Vector Error Correction Model

The *vector error correction model* (VECM) is suitable for analysing the lead-lag relationship between futures and spot markets, since the no-arbitrage principle suggests that these two variables have a linear equilibrium relationship (Stock 1987). Statistically, when two time series are co-integrated, their co-integrating vector describes the long-run equilibrium conditions to which the variables tend to return. The theoretically robust no-arbitrage principle corresponds to the long-run equilibrium, i.e. when the time series eventually return whenever they move apart. VECM captures simultaneously the short-term and long-term inter-market movements and allows

⁴ $F = \frac{(RSS_1 - RSS_2)/(p_2 - p_1)}{RSS_2/(n - p_2)}$, when model 1 is within model 2, i.e. restricted model. RSS is the

residual sum of squares, p is the number of parameters and n is the number of cases. The null hypothesis is rejected if F is greater than the critical value with desired level of significance. (Bartholomew 1981.)

examining whether returns from one market move towards returns in another market or vice versa. (Granger and Newbold 1986: 224-226.)

Furthermore, there is a relationship between error correction models and co-integration. It was first suggested by Granger (1981), and further investigated by Granger and Weiss (1983). The idea is that the residuals from regression (27) can be used to estimate the error correction model for two time series that are $CI(1,1)$ (Engle and Granger 1987). The variables will thus have the following error correction form:

$$(32) \quad \Delta Y_t = \alpha_1 + \alpha_Y e_{t-1} + \sum_{i=1}^q \alpha_{11}(i) \Delta Y_{t-i} + \sum_{i=1}^p \alpha_{12} \Delta X_{t-i} + \varepsilon_{Yt}$$

$$(33) \quad \Delta X_t = \alpha_2 + \alpha_X e_{t-1} + \sum_{i=1}^q \alpha_{21}(i) \Delta Y_{t-i} + \sum_{i=1}^p \alpha_{22} \Delta X_{t-i} + \varepsilon_{Xt}$$

where

Δy_t = S&P 500 or DJIA returns;

Δx_t = SP or DJ returns;

e_{t-1} = the residual from equation (27);

ε_{Yt} and ε_{Xt} are white noise disturbances;

q and p are lag parameters;

$\alpha_1, \alpha_2 \dots \alpha_{22}$ are all parameters.

Except for the error correction term (ECT) e_{t-1} equations (32) and (33) constitute a VAR model. Therefore, the error correction model can be estimated using VAR methodology. Furthermore, OLS is an efficient estimator in this case since both equations contain the same set of regressors. (Granger and Newbold 1986: 224-226.)

5. EMPIRICAL ANALYSIS

This chapter reports the findings gathered in this study. The research data and the methodology from which the research evidence is obtained are explained in the previous chapter. The precise analysis of the research data will also be displayed. Furthermore, some solely theoretical reasons behind the possible lead-lag relationship between stock and futures markets are discussed.

5.1. Properties of the Time Series

Before investigating the contingent lead-lag relationship between the futures and the spot markets, a closer look into the data needs to be conducted. The time series have to be statistically analysed and also tested for unit root and co-integration.

5.1.1. Descriptive Statistics and Autocorrelation

The descriptive statistics for all the eight time series are presented in Table 1. It can be

Levels				
	S&P 500	DJIA	SP	DJ
n	12484	12484	12484	12484
Mean	967,6590	9140,2866	967,0185	9125,1215
Variance	35039,5920	2240000,0000	35373,6200	2264000,0000
Std. Dev.	187,1887	1496,5933	188,0788	1504,6383
Min	667,0400	6473,3000	666,3000	6466,0000
Max	1312,7000	11860,0000	1313,0000	11850,0000
Skewness	0,6220	0,4410	0,6190	0,4470
Excess Kurtosis	-1,0310	-1,0390	-1,0460	-1,0550
Returns				
	S&P 500	DJIA	SP	DJ
n	12484	12484	12484	12484
Mean	0,0000	0,0000	0,0000	0,0000
Variance	0,0000	0,0000	0,0000	0,0000
Std. Dev.	0,0035	0,0031	0,0035	0,0033
Min	-0,0503	-0,0553	-0,0713	-0,0597
Max	0,0434	0,0453	0,0566	0,0415
Skewness	-0,2340	-0,3200	-0,2170	-0,3230
Excess Kurtosis	23,7750	28,6210	42,5360	30,3830

Table 1. The descriptive statistics of the time series.

seen that for the levels mean, variance and standard deviation are all reasonably high throughout the time series. At the same time, the excess kurtosis has a small absolute value for all the levels.

For the returns, however, mean, variance and standard deviation all approach zero as the excess kurtosis increases. This is a very logical observation as the return time series have a low, even distribution. For the levels the distribution is more concentrated near the mean. (Wilmot et al. 1996: 23-24.)

Furthermore, it is also essential to test the returns time series for *autocorrelation*. Autocorrelation describes the correlation between values of a stochastic process at different points in time. It indicates the extent to which one value of the process is correlated with previous values. To some extent, it can be used to measure the length and strength of the process's memory, i.e. how much a value taken at time T depends on that at time $T-t$. (Granger and Newbold 1986: 5-6.)

Returns				
Autocorrelation	S&P 500	DJIA	SP	DJ
1 lag	0,000	-0,023	-0,038	-0,018
2 lags	-0,022	-0,037	-0,016	-0,044
3 lags	-0,005	0,010	-0,005	-0,017
4 lags	-0,003	-0,029	-0,019	-0,022
5 lags	0,009	0,012	0,018	0,017
6 lags	0,000	0,009	-0,015	-0,007
Ljung-Box	S&P 500	DJIA	SP	DJ
1 lag	0,001	6,740 *	18,347 ***	3,849
2 lags	5,962	23,622 ***	21,782 ***	27,825 ***
3 lags	6,249 *	24,777 ***	22,086 ***	31,365 ***
4 lags	6,384	35,533 ***	26,740 ***	37,474 ***
5 lags	7,392	37,187 ***	30,922 ***	41,148 ***
6 lags	7,392	38,291 ***	33,741 ***	41,827 ***
* Significant at 0,10 level				
** Significant at 0,05 level				
*** Significant at 0,01 level				

Table 2. Autocorrelations and Ljung-Box test statistics for the return time series.

A good test detecting autocorrelation in time series is the Ljung-Box test⁵. It tests the null hypothesis that all autocorrelations for a process are combined zero with m number of lags. Further, according to the null hypothesis the obtained Ljung-Box test statistic is χ^2 distributed with m degrees of freedom. The autocorrelations and Ljung-Box test statistics with 6 lags for the return time series can be seen in Table 2. (Ljung and Box 1978.)

From Table 2 the first observation is that the return time series are reasonably autocorrelated. The level of autocorrelation, however, fluctuates slightly between the time series. By far the least autocorrelated time series is the S&P 500 index, showing only little autocorrelation with 3 lags. Meanwhile, the most autocorrelated time series is the SP futures, having significant autocorrelation with all 6 lags. Generally, the autocorrelation seems to be smallest with 1 lag, increasing with descendent rate as the number of lags increases.

The existence of autocorrelation in the data set does tend to robust the later achieved research results. It can cause the significance of a regression model used to be overestimated. However, autocorrelation in financial time series is rather common. Mostly, in return time series, it means that the future values are somewhat predictable from past values. (Granger and Newbold 1986: 5-6; Chan 1992.)

5.1.2. Testing for Unit Root

Time series analysis is, in general, based on analysing stationary variables. Therefore we need to examine the stationarity and existence of unit root in the time series with the ADF-test. Table 3 shows the results for testing the null hypotheses of a unit root in levels and returns, respectively for all time series. The critical values are provided by MacKinnon (1991).

From the above results it can be clearly seen that the existence of unit root in levels can not be ruled out. The ADF-test does not reject the null hypothesis of unit root even at the 10 percent level. This is quite normal for economic time series of levels (Engle and Granger 1987).

⁵ $Q = n(n + 2) \sum_{k=1}^m \frac{\hat{\rho}_k^2}{n - k}$, where n is the sample size, m is number of lags being tested and $\hat{\rho}_k$ is the sample autocorrelation at lag j . For more, see Ljung and Box (1978).

However, the results for return time series indicate clear stationarity. ADF-test has significant values at the 1 percent level for all the four time series. Therefore, the null hypothesis of unit root can be rejected.

Levels				
Stationarity	S&P 500	DJIA	SP	DJ
ADF	-1,514	-1,06	1,608	-1,923

Returns				
Stationarity	S&P 500	DJIA	SP	DJ
ADF	-4,452 ***	-4,262 ***	-4,324 ***	-5,086 ***

* Significant at 0,10 level (-2,567)
 ** Significant at 0,05 level (-2,862)
 *** Significant at 0,01 level (-3,434)

Table 3. Stationarity of levels and returns.

5.1.3. Testing for Co-integration

Since the variables seem to be integrated of the same order, it remains possible that they are co-integrated. Co-integration can be tested by examining the stationarity of the residuals from equation (27). For the variables to be in long-run equilibrium, the equilibrium error process has to be stationary.

Residuals				
Stationarity	S&P 500 ~ SP	SP ~ S&P 500	DJIA ~ DJ	DJ ~ DJIA
ADF	-41,328 ***	-46,587 ***	-46,231 ***	-45,429 ***

* Significant at 0,10 level (-3,047)
 ** Significant at 0,05 level (-3,338)
 *** Significant at 0,01 level (-3,901)

Table 4. Stationarity of residuals.

Table 4 shows the results of the ADF-test applied on the residual sequence of the equation (27). The critical values are again provided by MacKinnon (1991). The results suggest significant stationarity for the residuals at 1 percent level. As the null hypothesis of unit root in the residuals is rejected, S&P 500 and DJIA are co-integrated

with SP and DJ, respectively. Given that all the levels time series were found to be $I(1)$, it can be concluded that time series are $CI(1,1)$.

As the Engle-Granger methodology does not suggest which are independent and which are dependent variables, results for both directions of the regression (27) are presented in Table 4. The methodology does not seem to be very sensitive to the direction of the regression, in this case at least, as the derived ADF-test statistics are very close to one another, both indicating strong stationarity.

5.2. Theoretical Reasons Behind the Lead-Lag Relationship

By viewing only the theoretical aspects, and not the empirical findings, a few reasons for the expectancy of futures prices leading those of spot can be discovered. First, when investors receive new information, they can choose whether to exploit it in the stock markets or in the futures markets. If the nature of the information is such that it only affects the share price of few companies, known as unsystematic information, investors will probably choose to trade those individual shares the information affects instead of the index futures, as the price movements in the individual stocks are much greater than the movements in the index. Nevertheless, if the nature of the information is such that affects economy in general, known as systematic information, investors are much more likely to trade index futures rather than the stocks. This is of course because of the many advantages trading futures has when compared to the trading of the underlying, including a very liquid market, low transaction costs, easily available short positions, good leverage and rapid execution (Subrahmanyam 1991). Therefore, futures price will respond to systematic, market-wide information first, while the unsystematic information will have little impact on the index or the futures prices. (Sutcliffe 2006: 162.)

However, when new information causes movements in the share prices of a large number of companies, affecting the price of the index, spot prices may lead futures prices. This can also occur when the futures are mispriced in relation to the spot, causing investors to exploit the stock market rather than the futures market. Thus, despite a strong general incentive for futures prices to precede spot prices, this may not always be the case, even with systematic information. (Sutcliffe 2006: 162.)

Second, even if the investors choose to trade mainly on the spot market, there is likely to be a delay in the response of the spot market to systematic information. As new systematic information arrives, investors will immediately amend the futures price accordingly, causing the next trade to reflect the new information completely. Meanwhile, for the spot to fully respond to the new information, assuming the index is computed from actualized prices rather than quotes, there must be a trade in every share of the index. Some indexes have up to 2 000 different shares. This suggests at least a substantial delay in the response of the index. (Sutcliffe 2006: 162–163.)

Finally, in some exchanges short selling of stocks can be difficult. An example of this is the uptick rule⁶ exercised in the USA. Therefore, bad news may first be reflected on futures prices and only later on the stock prices, as short positions in futures markets are easy to assume. (Sutcliffe 2006: 163.)

In addition, as the index and the futures contract differ with respect to the times at which they value the shares in the index, the price of futures contract can be the source of additional information. A stock index represents the estimate of present value of the cash flows expected from the companies that constitute the index, while the current price of index futures contract with maturity T represents the estimate of the present value of the subsequent cash flows at time T . Therefore, the additional information contained in the futures price, over that contained in the spot price, is the value of the cash flows from owning the index between now and then. (Carlton 1984.)

5.3. The Empirical Results of the Lead-Lag Relationship

After thorough examination of the data, including evaluation of the time series properties, and discussion about the theoretical reasons suggesting lead-lag relationship between futures and stock markets, an empirical investigation where the research hypotheses are tested can take place. First presented are the results from testing the Granger causality theorem, and the regression results from the VECM are to follow.

⁶ The uptick rule is a securities trading rule used to regulate short selling in financial markets. The rule mandates, subject to certain exceptions, that when sold, a listed security must either be sold short at a price above the price at which the immediately preceding sale was affected, or at the last sale price if it is higher than the last different price. It is more formally known as rule 10a-1.

In order to test the hypotheses with these two methods, the number of lags for the regression parameters needs to be decided. For the sake of generality, 6 lags for the own market and 6 lags for the other market are chosen. Thus, the values for q and p in the equations (30), (31), (32) and (33) run from 1 to 6. This corresponds to a lead-lag time period of 30 minutes. It should be possible to detect any apparent lead-lag relationship in that time period, as many previous studies (e.g. Stoll and Whaley 1991; Chan 1992) have found the lead or lag to be less than 30 minutes, and that modern trading technology only shortens the leads and lags (Frino and McKenzie 2002).

5.3.1. Results for Granger Causality Theorem

Results from testing the Granger causality theorem on the two stock index returns and the two futures returns can be found from Table 5. They show a very clear two-way causal relation between the stock indexes and stock index futures. Three of the four null hypotheses can be rejected with 0,1% significance level with all values of q and p . The one remaining null hypothesis can also be rejected with at least 10% significance level in 86,11% of the cases with different combinations of q and p .

However, the results in Table 5 are somewhat surprising. They seem to suggest that the causal relation runs stronger from the indexes to the futures than vice versa. This creates an incongruity with the majority of the existing research, and with the theoretical aspects of a lead-lag relationship. Furthermore, the causal relation seems to also fluctuate very intensely throughout the data period because all the null hypotheses are rejected with very high significance. This indicates strong uncertainty during the data period on both the stock and futures markets, causing them to move rather inconsistently in relation to one another.

The causal relation seems to be stronger between DJIA and DJ than between S&P 500 and SP. The strongest causal relation runs from DJIA to DJ and the weakest from SP to S&P 500. Although the F values in all the four cases seem to decrease slightly when both lags increase, thus indicating that the predictive power of the other market weakens as own lags are taken into account, it alone is not solid enough evidence to further analyse the behaviour of the lead-lag relationship between the two markets. The behaviour and strength of the lead-lag relationship can be better investigated with the VECM in the next chapter.

Returns**Granger Causality****SP does not cause S&P 500**

Lags	OWN	F-test 1	F-test 2	F-test 3	F-test 4	F-test 5	F-test 6
OTHER							
1		2,267	3,408*	2,629 *	2,141 *	1,967 *	1,687
2		2,168 *	4,993 **	4,035 **	3,397 **	3,072 **	2,688 **
3		1,630	4,033 **	5,032 ***	4,333 ***	3,930 ***	3,493 ***
4		1,565 *	3,559 **	4,363 ***	3,883 ***	3,569 ***	3,212 ***
5		1,508	3,262 **	4,025 ***	3,607 ***	3,264 ***	2,967 **
6		1,352	2,895 **	3,604 ***	3,271 ***	2,984 ***	2,968 ***

S&P 500 does not cause SP

Lags	OWN	F-test 1	F-test 2	F-test 3	F-test 4	F-test 5	F-test 6
OTHER							
1		61,953 ***	45,364 ***	34,174 ***	28,515 ***	24,174 ***	20,997 ***
2		43,436 ***	36,101 ***	29,185 ***	25,339 ***	22,032 ***	19,543 ***
3		32,584 ***	28,897 ***	26,040 ***	23,627 ***	20,918 ***	18,863 ***
4		26,415 ***	24,358 ***	22,593 ***	24,630 ***	21,913 ***	20,004 ***
5		22,404 ***	21,209 ***	20,062 ***	22,089 ***	20,869 ***	19,455 ***
6		19,306 ***	18,665 ***	17,928 ***	19,961 ***	19,061 ***	19,602 ***

DJ does not cause DJIA

Lags	OWN	F-test 1	F-test 2	F-test 3	F-test 4	F-test 5	F-test 6
OTHER							
1		6,132 ***	11,433 ***	8,760 ***	9,240 ***	7,944 ***	6,918 ***
2		9,393 ***	8,641 ***	7,032 ***	7,720 ***	6,828 ***	6,070 ***
3		7,194 ***	7,015 ***	7,712 ***	7,661 ***	6,889 ***	6,198 ***
4		6,572 ***	6,496 ***	7,232 ***	6,804 ***	6,171 ***	5,622 ***
5		6,527 ***	6,552 ***	7,107 ***	6,786 ***	7,082 ***	6,438 ***
6		5,909 ***	5,970 ***	6,591 ***	6,334 ***	6,609 ***	6,847 ***

DJIA does not cause DJ

Lags	OWN	F-test 1	F-test 2	F-test 3	F-test 4	F-test 5	F-test 6
OTHER							
1		195,236 ***	139,518 ***	105,890 ***	86,802 ***	72,742 ***	62,645 ***
2		130,148 ***	135,199 ***	109,418 ***	93,185 ***	80,096 ***	70,400 ***
3		97,604 ***	109,535 ***	113,622 ***	99,537 ***	87,206 ***	77,965 ***
4		80,377 ***	93,208 ***	97,543 ***	91,436 ***	81,331 ***	73,679 ***
5		67,103 ***	79,950 ***	85,400 ***	81,798 ***	74,509 ***	68,242 ***
6		57,594 ***	70,018 ***	75,937 ***	73,640 ***	67,856 ***	68,123 ***

* Significant at 0,100 level

** Significant at 0,010 level

*** Significant at 0,001 level

Table 5. Results from testing Granger causality theorem.**5.3.2. Results for Error Correction Term**

Overall, ECT proves to be a rather good indicator for the lead-lag relationship. Table 6 reports all the estimated ECTs and their significance levels. There is distinct display of a lead-lag relationship between S&P 500 and SP, and DJIA and DJ, respectively. Like

Returns

Estimation of Error Correction Term

Dependent S&P 500

Lags	OWN	t-value	t-value	t-value	t-value	t-value	t-value
	1	2	3	4	5	6	
OTHER							
1		2,910 **	2,890 **	2,905 **	2,896 **	2,863 **	2,862 **
2		2,937 **	2,605 **	2,620 **	2,609 **	2,576 **	2,576 **
3		2,941 **	2,589 **	2,461 *	2,453 *	2,419 *	2,420 *
4		2,916 **	2,566 **	2,452 *	2,474 *	2,440 *	2,441 *
5		2,883 **	2,527 *	2,409 *	2,429 *	2,422 *	2,423 *
6		2,872 **	2,518 *	2,402 *	2,422 *	2,417 *	2,459 *

Dependent SP

Lags	OWN	t-value	t-value	t-value	t-value	t-value	t-value
	1	2	3	4	5	6	
OTHER							
1		4,441 ***	4,658 ***	4,676 ***	4,765 ***	4,785 ***	4,815 ***
2		4,442 ***	5,348 ***	5,419 ***	5,523 ***	5,532 ***	5,572 ***
3		4,440 ***	5,346 ***	6,184 ***	6,428 ***	6,430 ***	6,484 ***
4		4,475 ***	5,379 ***	6,230 ***	7,365 ***	7,355 ***	7,422 ***
5		4,495 ***	5,399 ***	6,250 ***	7,375 ***	7,821 ***	7,970 ***
6		4,516 ***	5,427 ***	6,280 ***	7,404 ***	7,858 ***	8,420 ***

Dependent DJIA

Lags	OWN	t-value	t-value	t-value	t-value	t-value	t-value
	1	2	3	4	5	6	
OTHER							
1		1,501	1,916 *	1,929 *	1,905 *	1,911 *	1,911 *
2		1,368	2,117 *	2,088 *	2,065 *	2,076 *	2,077 *
3		1,345	2,091 *	1,530	1,613	1,624	1,628
4		1,288	2,025 *	1,448	1,782	1,756 *	1,760 *
5		1,324	2,084 *	1,518	1,872	2,320 *	2,320 *
6		1,321	2,076 *	1,499	1,847	2,289 *	1,958 *

Dependent DJ

Lags	OWN	t-value	t-value	t-value	t-value	t-value	t-value
	1	2	3	4	5	6	
OTHER							
1		2,289 **	2,392 **	2,407 **	2,473 **	2,491 **	2,507 **
2		2,288 **	2,447 **	2,464 **	2,535 **	2,549 **	2,566 **
3		2,289 **	2,496 **	3,148 **	3,234 **	3,244 **	3,270 **
4		2,339 **	2,546 **	3,151 **	3,474 ***	3,480 **	3,511 ***
5		2,338 **	2,546 **	3,150 **	3,493 ***	3,490 ***	3,524 ***
6		2,345 **	2,552 **	3,154 **	3,497 ***	3,499 ***	3,929 ***

* Significant at 0,100 level

** Significant at 0,010 level

*** Significant at 0,001 level

Table 6. Results from VECM.

already anticipated from the Granger causality results, there is strong evidence the two indexes lead their two corresponding futures. Also, evidence of the futures leading the indexes exists.

The lead-lag relationship seems strongest between S&P 500 and SP. S&P 500 has a very powerful lead over SP in all the lags, as 100% of ECTs explaining SP returns were

significant at 0,1% level. This suggests a meaningful lead up to at least 30 minutes. On occasion, SP also has a rather strong lead over S&P 500, but the lead seems to weaken after two lags, corresponding to a lead-time of 5 to 10 minutes. ECTs explaining S&P 500 returns are significant at 1% level for the first two lags, but as the lags increase the significance level drops to 10%.

Returns

Adjusted R Square (from VECM regression)

Dependent S&P 500

Lags	OWN	1	2	3	4	5	6
OTHER							
1		0,001	0,003	0,003	0,003	0,004	0,004
2		0,002	0,003	0,003	0,003	0,004	0,004
3		0,002	0,003	0,003	0,004	0,004	0,004
4		0,002	0,003	0,004	0,004	0,004	0,004
5		0,003	0,003	0,004	0,004	0,005	0,005
6		0,003	0,003	0,004	0,004	0,005	0,006

Dependent SP

Lags	OWN	1	2	3	4	5	6
OTHER							
1		0,031	0,033	0,033	0,034	0,034	0,034
2		0,030	0,042	0,042	0,043	0,043	0,043
3		0,030	0,042	0,052	0,053	0,053	0,053
4		0,031	0,043	0,052	0,056	0,056	0,056
5		0,031	0,043	0,052	0,056	0,056	0,057
6		0,031	0,043	0,052	0,056	0,056	0,062

Dependent DJIA

Lags	OWN	1	2	3	4	5	6
OTHER							
1		0,001	0,001	0,001	0,001	0,001	0,001
2		0,001	0,002	0,002	0,002	0,002	0,002
3		0,001	0,002	0,002	0,002	0,002	0,002
4		0,001	0,002	0,002	0,002	0,002	0,002
5		0,001	0,002	0,002	0,002	0,002	0,002
6		0,001	0,002	0,003	0,002	0,002	0,002

Dependent DJ

Lags	OWN	1	2	3	4	5	6
OTHER							
1		0,011	0,012	0,012	0,012	0,012	0,013
2		0,011	0,013	0,013	0,014	0,014	0,014
3		0,011	0,013	0,015	0,015	0,015	0,016
4		0,011	0,013	0,015	0,019	0,019	0,019
5		0,011	0,013	0,015	0,019	0,020	0,020
6		0,011	0,013	0,015	0,019	0,020	0,023

Table 7. Adjusted R² values from VECM regression.

Furthermore, DJIA also has an intense lead over DJ. ECTs explaining DJ are significant at least at 1% level for all the lags. However, there seems to be minor strengthening of the lead at later lags, implying a lead-time of 20 to 30 minutes at least. There is weak

evidence of DJ leading DJIA, but the lead appears to be very inconsistent and last only one or two lags, suggesting a lead of 5 to 10 minutes. Furthermore, ECTs explaining DJ do not receive a higher significance level than 10% in any lag.

Moreover, the adjusted R^2 gathered from the VECM regressions further confirms the results from the ECT estimations. Presented in Table 7, the values for the adjusted R^2 are in line with the estimated ECTs explaining the variables.

They show the strongest lead from S&P 500 to SP and the weakest lead from DJ to DJIA. The median values of the adjusted R^2 are reported in Table 8. Overall, the R^2 values are greater when the futures are as dependent variables.

Returns

Median Adjusted R Square (from VECM regression)

Dependent	S&P 500	SP	DJIA	DJ
Median	0,004	0,048	0,002	0,032

Table 8. Median R^2 values from VECM regression.

5.4. Evaluation of the Research Hypotheses

After analysing the empirical results of this study, a look back at the research hypotheses can be made. The four research hypotheses are presented in chapter 1. As the results for the Granger causality theorem and VECM both suggest, there is a lead-lag relationship between S&P 500 and SP and DJIA and DJ. This leads to the competent acceptance of hypotheses H_1 and H_2 , respectively.

Furthermore, there also exists strong evidence that during times SP leads S&P 500, and weak evidence that at certain points in time DJ leads DJIA. Thus, the two remaining hypotheses H_3 and H_4 can be accepted as well. Finally, it can be concluded that all four research hypotheses are accepted based on the empirical analysis conducted on the research data.

6. CONCLUSIONS

This thesis investigates the linkage between American stock and futures markets by studying the lead-lag relationship between S&P 500 and DJIA indexes and their corresponding futures SP and DJ. The study is conducted analysing 5-minute intraday returns over a sample period of 8 months running from August 2008 to March 2009. As the two markets are bonded by evident long-run equilibrium in concordance with the no arbitrage theory, the aim is to find out whether there exists a detectable and predictable lead-lag pattern whenever the stock and futures prices move apart from each other. The stock and futures returns are studied with the Granger causality theorem and VECM, respectively.

The main findings are that there exists a two-way causal relation between S&P 500 and SP and DJIA and DJ. Furthermore, a strong lead for both the indexes over the two futures is detected. There is also evidence of the two futures leading the two indexes at certain times. The causal relation, however, runs far greater from stock market to futures market than vice versa.

Contrary to most of the previous research, this study found the stock market to precede the futures market in the majority of the time when the markets do not move contemporaneously. Another discovery made that is not supported by the bulk of existing literature is that the lead-lag relationship between stock and futures markets seems to fluctuate and change direction rather intensely. Overall, the lead-lag relationship seems more unstable than previous studies have found it to be.

The results show that S&P 500 has a strong lead over SP up to at least 30 minutes. On occasion the SP also has a rather strong lead over S&P 500, but this lead seems to only be 5 to 10 minutes long. Furthermore, the results also show that DJIA has a strong lead over DJ lasting up to 30 minutes, but intensifying even more after 20 minutes. DJ has only a weak 5 to 10 minute lead over DJIA. These results indubitably lead to the acceptance of all four research hypotheses.

As for the reasons why the findings of this thesis to some extent differ from the findings of previous works, the contemporaneousness of the data period and the global economic recessions is presumably the most important one. It is clear the recession has indeed had an influence on the financial markets, making them more unstable and harder to predict.

This has of course inevitably had an influence on the United States stock and futures markets, and inevitably on the lead-lag relationship between them. The relationship has become more imbalanced and more inconsistent.

Perhaps, as the investors direct their assets away from riskier instruments and target as risk-free investments as possible during these uncertain times, the stock market seems more tempting than the derivatives market. Albeit that stock markets have also been subject to significant uncertainty and major decline in value, maybe the investors trading stock have more knowledge of their investment targets and more long-term patience after all. Many of the previous studies that have found futures to lead stock have attributed the lead to futures contracts' more liquid markets and better transaction qualities. Possibly these effects have had less influence during the recession as futures' open interests have reduced and transactions have declined significantly in volume.

Furthermore, some of the preceding research has found futures markets to be the origin of new market-wide information as it streams to the stock market, and explained the futures' lead with this. It might be that when the systematic information is mainly unfavourable and also possibly more intricate and harder to interpret, the investors trading futures have dissonance of the price they should trade, thereby causing the market to move inconsistently with regard to the stock market.

Also, when speculators tend to move away from the futures market as it proves too risky during the recession, hedgers may settle for a price under or over the market in fear of their investments. Hedgers follow the stock market more closely and the depart of speculators can swing the lead-lag relationship around. When the stock market falls constantly there can be notable lack of investors willing to take long position on stock index futures, as hedgers prefer the short position. This is suited to cause the stock market's lead. Additionally, the insecurity of the speculators might also in part explain why the lead-lag relationship is so unstable during the recession.

The differences in the lead-lag relationships between S&P 500 and DJIA can as well in part be due to the rapidly falling stock market. As DJIA only has the stocks of 30 companies compared to the stocks of 500 companies in S&P 500, it is easier to predict the direction of S&P 500. DJIA is also a price-weighted index while S&P 500 is a capitalization-weighted index. At least in theory it can be argued that the direction of DJIA is more vulnerable for fluctuation because a sudden increase in the value of only few major stocks can weaken the index's decline or even turn it into incline, while the

rest of the market is falling rapidly. This can cause contradiction for some of the investors who might want to take long position in DJ contracts. This contradiction can result in a weak lead of the DJ for a short period of time, whereas the SP has a strong lead over S&P 500 for brief moments whenever the stock market settles down from the decline.

Prolific research avenues for the future would be to study the lead-lag relationship after the global recession is over and see whether the relationship returns to the same pattern than before the recession. Moreover, studies examining the lead-lag relationship through the volatility of the stock and futures markets might also have interesting findings, as the volatility distinctly rises during uncertain times.

Furthermore, by conducting the research with different methods and in other markets than American, one could find out whether the recession has had altered effects around the world. Also, by adjusting the data period so that it lasts only the most critical part of the recession or comparing the lead-lag relationship within the recession, it would be possible to find out whether the truly worst times differ from the milder times of the recession.

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