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Derivatives market before and after the financial crisis

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Abstract

Volatility in financial markets plays a very important role in making or wrecking the fortunes of investors. The study of volatility has attracted growing attention by researchers and policy makers since it is a measurement of risk, especially during extreme conditions such as financial crisis. This thesis through four models based on the opening, closing, high and low prices analyses and compares the volatility before and after the financial crisis of 2008. The global financial crisis initiated in the United States in early 2008 and then the financial meltdown had spread to the rest of the world. The study has been conducted on NASDAQ-100, FTSE-100 spot price indices, E-mini NASDAQ-100 and FTSE-100 Index Future futures price indices. Furthermore, this thesis examines the existence of the 'monthly effect' on returns and in volatility in U.S. and UK spot and futures markets between January 2006 and March 2019. The data have been partitioned into two sub-periods which allowed us to test the presence of monthly effect on returns or in volatility over the periods of pre-crisis (pre-2008) and post-crisis (post-2008).

The sample employed in this dissertation comprise 3333 daily observations on NASDAQ-100, FTSE-100 spot price indices, E-mini NASDAQ-100 and FTSE-100 Index Future futures price indices. The set period of study was from 3 January 2006 to 4 March 2019. The results show that a simple measure of volatility (defined as the logarithmic difference between the high and low prices) overestimates the other three volatility estimators. The means of volatility estimators seem to have higher values during post-2008 period compared to pre-2008 period. Furthermore, the results from an OLS model show that there is no January effect in the UK and the US during the entire period and the two sub-periods. Regarding the impact of January effect in volatility of spot and futures indices, the hypothesis of January effect in volatility is accepted for FTSE-100 cash and stock index futures markets over the sub-period 2006-2007.

Keywords: Volatility, High price, Low price, Open price, Closing price, monthly effect, US, UK, financial crisis.

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Last but not least, I would like to express my deep and sincere gratitude to my family and dedicate this thesis to my father who passed away the previous year.

Contents

CHAPTER 1
Introduction

Financial derivatives are securities, with a value that is dependent upon or derived from one or more underlying assets, used to reduce or hedge risks. Their value is determined by fluctuations of the values of the underlying asset. Very often the financial assets underlying derivatives are the prices of traded assets. For example, a stock option is a derivative whose value depends on the price of a stock. Furthermore, the last years many new types of derivative products have been created, from stock index futures, swaps, options and forward contracts to insurance and energy derivatives.
The major innovation of the introduction of derivatives on stock index futures in April 1982 have had an enormous impact on financial transactions. The derivatives exchanges have provided market participants flexibility, concerning the quickness in their transactions. As a result, a noteworthy number of transactions have shifted from spot to futures markets. Today, it is obvious that an impressive trading growth has taken place in the field of derivative products. After four decades of enormous expansion of financial markets the notional amount of derivatives traded in the over-the-counter (OTC) market rose to 640 trillion US dollars at end-June 2019 and the notional amount of exchange-traded futures and options as of September 2019 was 110 trillion US dollars (BIS,2019). Thus, today financial markets are able to facilitate the trading of huge amounts of assets, goods and money minimizing the risk for the financial institutions.
The impact of futures on stock market is still debatable after the introduction of futures market. The relationship among stock and futures markets and the interactions between them have been an area of intense interest and investigation to financial analysts, researchers and practitioners. Previous studies show that the futures market leads the stock market (Stoll & Whaley, 1990). The lower transactions costs in the futures market make it more advantageous for investors to trade index futures as a result the financial markets may lead the returns of the stock market. Furthermore, the literature presents arguments that futures markets affect stock market volatility and some previous studies suggest cannot conclude clearly whether the introduction of futures stabilizes or destabilizes the underlying spot market. Empirical studies for US and UK financial markets cannot deduce explicitly if stock index futures trading lead to increased or decreased stock market volatility. In addition according to Antoniou and Holmes (1995) the arrival of futures trading depends on speculators' information and when speculators have a noisy signal the introduction of futures markets destabilize prices. But when speculators have perfect information, there is a stabilizing effect on underlying spot share market.
The global financial crisis initiated in the United States in early 2008 and the largest one day drop in market stock prices since Dow Jones began computing index numbers happened on September 29, 2008 when Dow Jones Industrial Average (DJIA) fell from 11,143 to 10,365 (over 777 points) (Schwert, 2011). Less than a month later, on October 13, 2008 the DJIA soared 936 points higher, to 9387.61, in one day. Large drops in stock and futures markets have been followed by large rises. This is characteristic of an increase in stock and futures market volatility.
Seasonal anomalies in spot and future market indices have attracted attention among both researchers and practitioners. Previous studies on the US stock markets report monthly seasonality and show that stock returns are significantly higher in January than in other months (January effect) (Dzhabarov & Ziemba, 2010).

The main objective of this dissertation is to analyze and compare the volatility before and after the financial crisis of 2008 along with the examination of the seasonal anomalies of spot and futures returns, using daily range data from the US & UK spot and futures markets covering two important sub-periods, i.e. pre-crisis (pre-2008) period, and post-crisis (post-2008) period. Hence, considering four volatility measures for US & UK stock and futures indices following the work of Floros (2009), the daily volatility using opening, closing, high and low prices from NASDAQ & FTSE-100 (stock indices (cash) and stock indices futures), namely NASDAQ-100 (US), FTSE-100 (UK) stock indices, E-mini NASDAQ-100 and FTSE-100 stock indices futures, will be examined. Furthermore, this study scrutinizes the highly volatile period by analyzing the monthly effect using an ordinary least squares model (OLS) and by evaluating the performance of several volatility estimators.
Specifically, the empirical findings of this dissertation can be summarized as follows. Initially, the empirical results clearly indicate that V_s, a simple measure of volatility defined as the logarithmic difference between the high and low prices, overestimates V_{gk}, V_p and V_{rs} and the means of volatility estimators seem to have higher values before financial crisis compared to the period after financial crisis.
Additionally, the results from an OLS model show that there is no January effect in the UK and the US. Regarding the impact of January effect in volatility of spot and futures indices, the hypothesis of January effect in volatility is accepted for FTSE-100 cash and stock index futures markets over the period before the financial crisis (2006-2007).
The rest of this dissertation is structured as follows: Chapter 2 discusses the review of the literature, while Section 3 provides the theoretical framework of derivatives. In Chapter 4 the UK & US spot and futures markets are presented, while Chapter 5 presents the methodology and Chapter 6 provides the data information. In Section 7, the empirical results of this study are presented and analyzed. Finally, the last section concludes the dissertation and summarizes all the findings.

CHAPTER 2
Literature Review

An extensive research has been conducted on the calculation of volatility based on high, low, open and closing prices by using several models. Additionally, numerous recent studies suggest that there is evidence of existence or non-existence of monthly effects. Various arguments have explained the existence of high stock returns in January (January effect).

The appearance of futures markets opened up new opportunities for investors, financial analysts and researchers. Futures contracts are attractive to investors since they have low transaction costs and margin requirements. Index futures contracts have several advantages over the underlying stock index. Several studies conclude that stock index futures markets incorporate information more quickly and efficiently than spot markets increasing the overall market depth (Chou & Chung, 2006 ; Bohl, et al., 2011). These are important for price discovery, enable the transfer of risk, play an important role in assesing market stability and may get lower spot volatility.

Global financial crisis of 2008 has impacted financial insitutions and markets substantially all over the world. The global financial crisis of 2008 emerged with the collapse of financial markets in the US, boosting cross-volatility spillovers across leading markets. As Antonakis et al. (2016) stated, 'the spot and futures volatilities in the UK (the US) are net receivers (net transmitters) of spillovers to volume of futures trading' and a strong evidence of bidirectional interdependence between spot and futures volatilities in the US and the UK do exist, which is affected by major economic events. Another related work on contagion explains the transmission of volatility among stock markets and reveals than the UK and German markets are affected by US market (Savva, et al., 2009). Slimane et al. (2013) explain the impact of the crisis on stock market behavior among three European stock markets (France, Germany and the UK) showing that the three indices (DAX-30, CAC-40 and FTSE-100) are highly intercorrelated, especially during the turbulent period and an increase of volatility during turmoil period mainly due to the interdependence of markets.

Reviewing the empirical literature, it is observable that the decision of the Chicago Mercantile Exchange (CME) to adopt a cash settlement mechanism instead of physical delivery provision of futures contract have effectively contributed to decrease price volatility, augment the contract's hedging performance and attract more interest. The above argument is supported by several previous studies including Kenyon, Bainbridge, Ernst (1991), Lien & Tse (2002) and Rich & Leuthold (1993). Chan and Lien (2003) employed in their study four volatility measures for futures price under the assumption of Geometric Brownian motion in order to examine the outcomes of the switching to a cash settlement procedure. The results of this study indicated that CME's shift to cash settlement decreases the volatility of volatility of the feeder catle futures price.

It should be mentioned that there has been significant focus on models that explain the observation of volatility clustering. The empirical examination include Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methodology, first introduced by Engle (1982) and stochastic volatility methodology (Hwang & Satchell, 2000). An important research is that of Floros (2009) who estimated volatility in the US using four models based on open,closing, high and daily prices and considering daily data from four US stock indices (S&P 100, S&P 400, S&P500 and S&P Small Cap 600). He concluded that daily prices from these US stock indices can be characterized by volatility models.

An enormous body of financial literature is available and suggests that calendar anomalies exist over current periods. The existence of monthly effects contradict the weak form of the Efficient Market Hypothesis (EMH) which assumes that stock prices reflect all available information. Basically, the monthly effect occurs when stock returns are not distributed equally across the months of the year. Various studies have supported the establishment of January effect when mean returns are higher compared to other months of year. These studies argue that it is better to invest at the beginning of the year since investors think about their tax liability and they sell their losers in December and then they buy them back in January to lock in a tax loss. In an early study the effect is found to be persistent with higher mean return as well as higher volatility in January (Rozeff & Kinney, 1976). According to Ritter and Chopra (1989) an explanation of the January effect is the portfolio rebalancing. Reinganum and Shapiro (1987) provided the evidence from the London Stock Exchange that the tax effect happened both in January since the individual invetsors choose April as the tax year. A January effect has also been found in US stock market (Choudhry, 2001). Rendon and Ziemba (2007) report a persistent January effect in the futures markets. In the Chinese and other Asian markets, Ho (1990) provided the evidence that the most of Asian countries have no January effect, although Zhang and Li (2006) report a strong January effect.

An other work examines the calendar effects and especially the evolution of the turn of the year on cash and futures markets (Szakmary & Kiefer, 2004). They report no abnormal returns during the turn of the year the post-1993 period and an evidence of a turn of the year effect in both cash and futures for the pre-1993 period. Additionally, Moller and Shlomo (2008) investigate the evolution of the January effect and their evidence shows higher abnormal returns in the first part of January and lower abnormal returns, offsetting each other, in the second part of month for the 1995-2004 period. In the Greek stock market, Floros (2008) shows that there is no January effect in ASE for all the three indices which examined for the period of 1996-2002. Giovanis (2009) investigate if there is certain seasonality on expected returns or in volatility and concludes rejecting monthly effects. In their survey Sun and Tong (2010), using a time-series GARCH framework with the conditional variance/covariance as proxies for systematic risk, find clear evidence that January effect is a phenomenon of risk compensation in the month.

The other prominent explanation for the January effect relies on the relationship between the phenomenon of January effect and firm characteristics. Haug and Hirschey (2006) contend that firm size plays an important role in determining the prominence of the January effect. More specifically, they argued that the effect is a small-cap phenomenon.

In addition to the many studies that have attempted to offer an explanation for the January effect, Shiller (1999) find that January effect relies on investors' behavioural biases. According to Shiller, investors tend to view the beginning of a year as a new opportunity.

Although there has been strong empirical evidence that supports the January effect, recent research report that the magnitude of the calendar anomaly has declined in the last decades. Mehdian and Perry (2002) study the DJIA, NYSE and S&P-500 and state that after 1987 January returns are not significant indicating that the calendar anomaly has disappeared in the US. Finally, Patel (2016), employing data from January 1997 to December 2014, suggest that January effect does not exist anymore in international stock returns.

Summarising it could be mentioned that seasonal effects on returns and volatlity along with modelling volatility are well known in the financial literature, but as far as the behaviour of investors and traders in futures and cash markets before and after the 2008 financial crisis has been given a little attention from past studies.

CHAPTER 3
Theoretical Framework

3.1 Derivative Instruments

3.1.1 The Derivatives Securities

The three major types of derivative securities are futures, options and swaps. The last three decades derivatives have become progressively paramount in the world of finance. Derivative securities are assets whose price derives from the prices of other, more basic underlying asset. Hence the derivative value depends on the value of this underlying asset.
Let's take as an example, a futures contract on Tesla stocks is traded on the Chicago Mercantile Exchange (CME). The underlying asset in this contract is the stock of Tesla itself, which is traded on NASDAQ. Today's futures price on Tesla stock quoted by CME is a price quote for delivery of Tesla stock in Chicago at a definite date in the future (Cuthbertson, et al., 2020). On the contrary, the price of the stock on the NASDAQ is for instant delivery of the stock named the cash or spot price. The strong relationship between spot and futures market price is due to risk-free arbitrage.

3.1.2 Overview of Futures Markets

Futures markets were introduced in order to annihilate and hedge risk in the cash market. The financial futures market began in 1972 when the Chicago Mercantile Exchange (CME) started trading futures contracts on foreign currency. The CME introduced the Standard & Poor's (S&P) 500 futures contract in 1982 and this was followed by the introduction of the New York Stock Exchange (NYSE) index futures contract by the New York Futures Exchange (NYFE).
Formally, a forward contract is an agreement between two parties to buy or sell a specific asset at a prespecified date in the future with certain terms and price, like a future contract. Futures contracts are normally traded on an exchange while forward contracts are traded in the over-the-counter market-usually between two financial institutions or between a financial institution and one of its clients (Hull, 2002). Thus, in contrast to forwards, which are specialized nontradeable agreements, futures can be very liquid financial instruments (Steland, 2012). The futures is a derivative security since every change in the cash market price of the underlying asset is closely linked to every change in futures price. Additionally, the futures derive their value from the value of a specified underlying asset. To make trading possible, futures exchanges provide the mechanism for facilitating the process that not only list a big number of contracts but gives the two parties a guarantee that the process-contract will be honored. The exchange specifies the period when delivery must be made (fixed maturity), the contract size and how the futures price is to be quoted. For some contracts physical delivery is not possible and cash payment is initiated. A futures contract can be bought and sold at any time till its delivery date and the hedger or speculator can take one of two positions on contract (long position-futures purchase, or a short position-futures sale). Futures allow trading in either direction, if a holder

think that the future asset price is going up, a trade will be opened with a buy order. The holder of the short position agrees to sell an asset at a specific price to profit from a falling future asset price, with the payment and delivery to occur on the expiration date. In a long position, one agrees to buy the contract's underlying asset at a specified price with delivery and payment occurring on the expiration date. Overall it is a zero sum game, ignoring transactions costs, since there is always a counterparty to a futures contract.

The corresponding price of the futures contract is the futures price. To provide contracts with merchantability, and in order to minimize default risk, futures exchanges use clearinghouses. The clearinghouses track all trades and guarantee each contract providing a financial protection, having an intermediary role that makes it easier for traders to close their positions before expiration and requiring from them to post collateral (e.g. T-bills, cash), known as a margin payment (Cuthbertson, et al., 2020). At each trading session all exchanges settle trades using computers and actual trades are conducted electronically, but some exchanges are also using open outcry (traders in the pit indicate prices by using hand signals). The investors have to deposit funds in a margin account and they have to pay initial futures margin, fixed by the exchange, which is the amount of money that is required to open a buy or sell position on a futures contract. The accounts in a futures contract are marked to market on a daily basis and the possible losses and gains are adjustable. The clearing house is responsible to proceed for all contracts with the clearing of the loss and the profit from the trading session. The holder of a long position makes a profit when the futures price rises that is exactly equal to the loss of the holder of the short position. As time goes by, the margin accounts reflect their daily losses and profits. The daily profit made by a winning party is credited to his margin account and debited from the margin account of the corresponding losing party. After the daily settlement, if the margin account falls below the maintenance margin, the investor's margin account have to be deposited by further funds since a margin call occurs. Consider a futures contract on gold with a value of $ 165,000, if gold futures price is at $ 1,650 per ounce. If the futures price increases by $ 10 (from 1,650 to 1,660) the value of one long futures contract changes by $ 1,000 and the value of one short holder decreases by $ 1,000.

The shape of the futures curve (futures contract price plot over time) is important for hedgers and speculators in order to shape their strategies. The state of the futures curve can be either in contango or backwardation. A futures curve is described as being in contango state when a futures contract price is above the expected future spot price, taking into account the time value of money (Greyserman & Kaminski, 2014). The investors in this situation may be willing to pay more for something in the future rather than what they should anticipate to pay. In contrast, the backwardation state refers to a case when futures price is below the expected future spot price.

3.1.3 Types of Futures Contracts & Clearinghouses

Futures contracts are now traded very actively all over the world. Currently the largest futures exchanges in the United States are the Chicago Mercantile Exchange Group (CME Group), after the merger with the Chicago Board of Trade (CBOT) closed on July 12, 2007, and the Intercontinental Exchange (ICE). Other large exchanges include Eurex, London International Financial Futures and Options Exchange and Tokyo International Financial Futures. These exchanges work approximately 23 hours per day, excluding weekends, and provide a centralized location for futures contracts in order to be traded on electronic trading platforms. Additionally, there are a lot of contracts offered by future dealers on the OTC market. There are many types of future contracts to choose, and they are classified as financial and physical futures. Financial futures trading usually refers to speculating on non-equity and equity indexes on bond, commodity, volatility, foreign currencies, and spread indexes and interest rate. From the other side, physical futures can include energy futures and futures with underlying asset a physical commodity. Physical commodities are broadly classified into metals and petroleum products, and agricultural that consist of grains, forest products, livestock, textile and foodstuffs. Large-scale financial institutions are more likely to carry speculative positions, while manufacturers and end users are more likely to conduct hedging transactions (Baker, et al., 2018). Finally, some of these contracts require physical delivery and others a cash settlement.

The clearinghouses associated with futures exchanges are an adjunct of the exchange and act as intermediaries in futures transactions that can guarantee each contract. Thus, the main task of the clearinghouse is to record all the transactions taking place during a day in order to calculate the net position of each of its members (Hull, 2002). The member of clearinghouse is required to have a clearing margin with the clearinghouse to ensure that the futures contracts can be delivered and the transactions will be completed, eliminating counterparty risk. In the same way that the margin accounts of investors work, the margin accounts for clearinghouse members are adjusted at the end of each trading day without maintenance margin. It is interesting to note that the clearing house is exposed to counterparty risk at maturity and this risk is covered by a system of collateral deposit.

3.1.4 Options Markets

Another important derivative is an option which is a security that gives the holder the right, but not the obligation, to take a long position to buy at a specified price on, or possible before, a specific date under certain conditions. These agreements are traded on stock indices, individual stocks, commodities, futures contracts, foreign currencies, Treasury bonds and notes. Nowadays, there are a vast number of options traded both on exchanges and in the over-the-counter (OTC) market. Exchange-traded options contracts are listed on exchanges such as the Philadelphia Stock Exchange (PHLX) and the Chicago Board Options Exchange (CBOE), the largest organized options market with a deep secondary market, in the US and Intercontinental Exchange in London. The exchange-traded options are standardized contracts, providing numerous benefits but also significant drawbacks, compared with the over-the-counter (OTC) options which are negotiated directly between the buyer and the seller. Additionally, exchange-traded options attract investors and portfolio manager since they are guaranteed by clearinghouses. In many cases, traders find OTC options advantageous to meet their trading needs since contracts can be customized to fit the holder's specific targets. However, two significant disadvantages to using the OTC market is the higher transaction cost as well as counterparty risk (Cuthbertson, et al., 2020).

There are two basic types of options, by definition a call option gives the holder the right to buy a specific asset or security by a certain date for a certain price, whereas a put option gives the holder the right to sell the underlying asset by a certain date for a certain price. The price in the contract is referred to as the exercise or strike price and is the price specified at which the underlying asset or security can be bought (call) or sold (put) at maturity which is the last day the holder can exercise.

The option buyer is referred to as the holder, and as having a long position in the option, buys the right to do something, exercise or invoke the terms of the option claim, but the holder is not obligated to exercise this right (Johnson, 2017). From the other side, the option seller has a short position and is responsible for fulfilling the obligations of the option if the holder exercises. From the aspect of association with the exercise date are American style options and European style options. These two features have similar characteristics but the key difference between them relates to when the options

can be exercised. Thus, a European option can be exercised only on the exercise date, while an American style option can be exercised at any time up to the expiration date. It has to be mentioned that there is a cost to acquiring an option whereas there are not costs to enter into a forward or futures contract. In the end, it has to be pointed out that any option contracts that grant the holder, of any style either European either American, can be sold to a third party, at any time prior to maturity.
Table {3.1} shows price quotes on a number of call and put options on AAPL (Apple Inc.) stock as of 17/4/2020, and expiration of April 24, accessed from the CBOE.

AAPL/Call-Put Options, 17/4/2020							
24/4/2020(7d)							
LAST	BID	ASK	Calls Strike	Puts Strike	LAST	BID	ASK
7.2	7.2	7.5	AAPL 280.000	AAPL 280.000	4.65	4.6	4.75
6	5.7	6.05	AAPL 282.500	AAPL 282.500	5.7	5.45	5.8
4.6	4.6	4.75	AAPL 285.000	AAPL 285.000	6.9	6.65	7.05
3.65	3.6	3.7	AAPL 287.500	AAPL 287.500	8.45	8.05	8.5

Table {3.1}: AAPL Stock Options for 17/4/2020 (7 Days to expiration)

As shown in table {3.1}, on 17/4/20, AAPL stock closed at $282.80, the AAPL call option with an exercise price of 285 and expiration of April 24 closed at 4.6 and dealers were offering to sell the option at 4.75 and to buy the option at 4.6.

3.1.5 Options Strategies

Consider the situation of an investor who buys a European call option and the current price of stock-ZYX on the NYSE on 15 June is $70. On 15 June somebody can pay the call premium $3 and buy an October-European call option on the stock-ZYX. The strike price in the contract (of 100 ZYX-shares) is $70 and maturity in just over four months' time on 26 October. So, the initial investment is $300. If the stock price on the expiration date is less than $70, the investor will choose to let the option to expire, since it will not be profitable, and to have a loss equal to the call premium. Thus, the maximum loss from the call purchase is $300 that was the initial investment. If the stock price is above $70 on the expiration date, the option will be exercised in the maturity date by paying the strike price. Suppose that the spot price is $77 on 25 October, then the holder of the call option can exercise the option contract, pay the strike price $70 per one stock (by taking delivery). If the investor wanted to sell immediately the stock for $77, the cash profit would be $7 per share. An alternative way could be the long call option to be cash settled for $7 which is paid via the clearing house without any stock to be delivered. Finally, the investor has a percentage return of 133.3% over a 4-month period.
When a speculator hold a call option and the stock prices increases at any time before the maturity date of the option leads to a speculative profit. This can be implemented by selling (shorting) the call option to another options trader, after the spot price has increased, closing out the initial long position in the option (Cuthbertson, et al., 2020). Thus, when the spot price of ZYX share increases that also drives to a rise in the call premium. For example, if stock-ZYX increases in price by $1.5 over one day that may change the call premium from $3 to $3.5. Hence, the speculator who purchased the October-call for $3 on 15 June, has the opportunity to sell the call on 16 June to another options trader for $3.25, making a return of 8.33% in just one day. The speculator closes out the contract and the $3.25 are received from the options clearing house.

Another strategy involves the sale of the call option in which the seller does not own the underlying stock (Johnson, 2017). This position is known as a naked call write. Consider the ZYX call option with the exercise price of $70 and the call premium of $3. When the spot price is at $81, the seller has a loss of $8 if the holder exercises the right to buy the stock from the writer at $81, since the writer does not own the stock. Thus, the net loss of $8 comes from the difference between the loss of $11 for the call writer and the $3 the premium received for selling the call. The break-even price for the writer and the holder is $73. Finally, when the spot price is $70 or less, the holder will not exercise and the writer will profit by the amount of the premium $3.
Whereas the purchaser of a call option realizes a profit when the stock price increases, for the purchaser of a put option profit is realized when the stock price is expected to decline in the future. A put option strategy can be used for speculation. The put holder can buy the stock at a lower price when the cash market declines, and afterwards to sell it at the higher strike price on the put contract. Consider an investor who purchases a European put option to sell 100 shares of stock-ZYX with a strike price of $82 and a put premium of $2.5, since the investor thinks that the stock price will fall in the future. Assume that the spot price decreases to $72, the put holder can purchase stock-ZYX and after immediately to use the put contract, with expiration date of the option in three months (and initial investment of $250), to sell the stock at the strike price of $82. Hence, the put holder realize a profit and receive $7.5 (per one share) and a break-even price of $79.5. Alternatively, in a case which the speculator cash settle the long put contract, clearing house will make a cash payment of $7.5 (per one share) when the long put contract is cash settled on maturity date. By using the long put contract to speculate on a future stock price fall, the speculator has made a percentage return of 200%, providing a leveraged return (Cuthbertson, et al., 2020). Suppose a final stock price above or equal to $82 at maturity, since the option is European it can be exercised only at the expiration date, the put option expires worthless, it will not be rational for the put holder to exercise, and as a result the investor will lose $250 that initially was paid for the put premium. Finally, similar to a call purchase strategy, a long put position provides the holder with potentially large profit opportunities, while reducing the losses to the maximum amount of the premium.
When the stock price is at $82 or more, the holder will not exercise and the writer will realize a profit equal to the amount of the premium $2.5. But if the spot price will be $77, the holder will exercise and the put writer has to buy the stock at $82. So, if the writer chooses to sell the stock having $5 loss and a paper loss that holds on it. When the cash market is $77 and the premium $2.5, this yield a loss of $2.5.
Another option strategy is the covered put write which requires the writing of put option, while shorting the (obligated) shares of the underlying stock. Since a put writer is required to buy the stock at the strike price of the put option if the holder exercises, the only way to cover this obligation is by selling the underlying equity short position. Let’s assume a writer of a YZX 82-put shorts a share of stock-YZX. If the spot price is less than the strike price at maturity and the put holder exercises, the covered put writer will buy the share with the $82, and after return the share to cover the short sale obligation with a profit of the premium call of $2.5. When the spot price is above $79.5 occur losses from the strategy of covered put write. Finally, losses will be incurred above $79.5, but they will always be $2.5 (per share) less than the stock trade alone.

3.2 Index Futures

3.2.1 Stock Index Futures

The first index based contract was introduced in 1982 on Kansas City Board of Trade which was the first exchange to offer trading equity index futures that led this type of futures contract to become very popular. So fast growing futures contracts have they become, that in many cases the volume of futures market trading transcends trading volumes in the associated underlying cash market (Loader, 2016). This was followed by the introduction of the Standard & Poor's (S&P) 500 futures contract, traded on CME and the New York Stock Exchange (BYSE) index futures contract and launched in January of 1983. In the US index futures contracts traded on the CME include those on S&P 500, the Mini-S&P 500, the Dow Jones Industrial Average (DJIA) and the Nikkei 225(Japanese index) and others. On London International Financial Futures and Options Exchange (LIFFE), part of NYSE-Euronext, futures exchange is available for various UK stock indices such as the FTSE 100 and FTSE 250 indices, on European indices including the FTSE Eurotop 100 and FTSE Eurotop 300 and others (Cuthbertson, et al., 2020). The S&P 500 contract is the most heavily traded equity index futures contract by notional value. The futures price on the S&P 500 futures is 2,843 on April 14, 2020, with a 250x multiplier and the expiration date is 19/6/2020. Generally, stock index futures are the only futures contracts having a variable contract size. The contract size equals to the multiplier (some amount of money) times the current underlying spot index value, whereas the variable contract value is defined by the multiplier times the current future price (marked to market).
For instance, on 19/05/2011, the available contracts for Euro Stoxx 50 futures were those of the next June, September, and December, as illustrated in Figure {3.1}. In the column "Open Int"-open interest is obvious that the vast majority (of 83.4%) refer to the nearest maturity of June indicating the enormous market interest along with the high number of still not closed contracts.

<HELP> for explanation. Index CT
1 <GO> to Configure Columns
View Futures | 1) Edit Columns | 2) Chart on CCRV | Contract Table
EURO STOXX 50 Pricing Date 05/19/11 Sort By Expiration
Eurex
Contracts 4/4 Tot Volume 788107 Open Int 2869474

Ticker		Last	Change	Time	Bid	Ask	Open Int	FairVal	Previous
3) SX5E	Spot	↑2905.53	+38.23	15:24					2867.30
4) VGM1	Jun11	↑2885.00	+39.00	15:24	2884.00	2885.00	2392974		2846.00
5) VGU1	Sep11	2885.00	+39.00	15:15	2883.00	2885.00	469844		2846.00
6) VGZ1	Dec11	2883.00	+42.00	14:57	2879.00	2881.00	6656		2841.00

Australia 61 2 9777 8600 Brazil 5511 3048 4500 Europe 44 20 7330 7500 Germany 49 69 9204 1210 Hong Kong 852 2977 6000
Japan 81 3 3201 8900 Singapore 65 6212 1000 U.S. 1 212 318 2000 Copyright 2011 Bloomberg Finance L.P.
SN 558826 CEST GMT+2:00 G771-1067-1 19-May-2011 15:24:54

Figure {3.1}: Euro Stoxx 50 futures: June, September and December contracts of 19/05/2011. *[Figure taken from Bloomberg]*

An index futures contract, like the S&P 500 index, allows investors and speculators to agree to buy (long) or sell (short) a portfolio of stocks composing the index at a fixed level and on a specified delivery date T. Most stock market indexes are capitalization-weighted indexes, including FTSE 100 index, S&P 500 index and the Nasdaq Composite Index (ISIC), ignoring dividend payments as a result they cannot absolutely mirror the total returns from the component shares that include dividends.
Such futures contracts has grown significantly over the last 37 years and these derivatives are widely used in index arbitrage, hedging and speculation. Index future contracts have a cash settlement feature, unlike many other futures contracts. An index futures seller (short position holder) has the obligation to sell a fixed amount of the underlying equity market, the cash equal to the closing spot index (S_T) on the delivery date at futures price (f_o), to the index futures purchaser (long position holder). The long position holder agrees to buy cash equal to the closing traded spot index (S_T) at maturity and at futures price (f_o). However, futures contracts are usually closed out prior settlement by an equal and opposite transaction. If $S_T<f_o$ the long position holder pays the futures seller a cash settlement of $S_T - f_o$ and if $S_T>f_o$ the short position holder pays the futures buyer the cash difference between the index price at maturity and the traded contract price. Finally, the unprecedented growth of these index derivatives contracts can be attributed to their usage as a stock portfolio management instrument.

3.2.2 Stock Index Futures Pricing

According to Cornell and French (1983) the futures price for a non-dividend paying stock must be equal to : $F(t,T) = S(t)e^{r(T-t)}$ (3.1)
Where S(t) is the stock price at time t, (r) is the risk-free interest rate, F(t,T) is the futures price at time for a contract with maturity at time T. However, this cost of carry model relies on some simplifying assumptions:

1) Capital markets are perfect
2) The risk-free borrowing and lending rates are equal and constant over time
3) Dividends don't exist

For a dividend paying stock case, their model becomes:
$F(t,T) = S(t)e^{r(T-t)} - \sum_{i=1}^{N} D_i e^{r(T-t_i)}$ (3.2)
Where the last component presents the dividend payment at time t_i compounded to the final settlement date of futures contract that are deducted from the index.
For the special case of a stock with a constant dividend yield (d), in continuous time, the futures price can be approximated by $(t,T) = S(t)e^{(r-d)(T-t)}$. (3.3)
Cornell and French (1983) examine this special case and support that dividends partially offset the interest cost of carrying stock portfolio.

3.2.3 Hedging Equity Positions

It is widely known that a well-diversified stock portfolio earn the highest return for the least risk, lowering the specific risk, while stock index futures contracts allow investors to hedge, stock portfolio positions, against alterations in stock market (market-'systemic' risk). This one of the major uses of stock index derivatives can be implemented by several different types of hedging models.
Stock index futures are used to hedge an equity portfolio. This leans on the positive correlation between futures and spot prices. If an investor hold an equity portfolio with

long position, then sorting stock index futures contracts has as a result a negative correlation between the possible gain on index futures position and the possible loss on his cash market portfolio. Generally, in some cases of hedging it is assumed that ideal conditions dominate the market in which there is no current timing risk and the value of spot position remains stable at expiration. In such rare cases, a prefect hedge can be accomplished by usage of naïve hedging model. In this model, the number of futures contracts (n_f) can be found simply by dividing the current value of the portfolio (spot position) (P) by the price of the stocks underlying the futures contract (f_o).

$$n_f = \frac{P}{f_o} \quad (3.4)$$

Suppose that a portfolio manager holds a $1 million diversified portfolio of US stocks which mirrors the index of the S&P 500 with hedge ratio of 1.0. He feels the stock market is likely to be very volatile but he is worried about a general fall and in order to eliminate the market risk uses stock index futures. The current value of the index futures is 2,000, and each futures contract has $250 multiplier. In this case two contracts should be shorted to hedge his stock portfolio. However, this is under ideal conditions and the stock portfolio may not be perfectly correlated with the S&P 500 spot index. In such a case, the naïve hedging model cannot provide a perfect hedge.
Assuming a more realistic scenario in which the portfolio does not exactly mirror the index, it can be shown that the appropriate hedge ratio is the beta of the portfolio. So the number of futures contracts or hedge ratio (n_f) that minimize the variability of profits is:

$$n_f = \beta \frac{P}{f_o} \quad (3.5)$$

where (β) is the beta of the stock portfolio.

3.3 The Relationship between Spot and Futures Prices

3.3.1 Dynamic Relationship & Literature Review

This subchapter covers the dynamic relationship between spot and futures market based on previous research. The literature has shown that there is a link between spot and futures markets that has become more and more complex.

Some past studies agree with hypothesis that futures prices lead spot prices since futures market respond to new information more quickly than the cash market mainly due to decreased transaction costs, flexibility of holding a short position and some investors who are not interested in the physical commodity or if they are interested and face storage constraints. Spot prices will react with a lag because spot transactions take longer to implement.

Herbst et al. (1987) presented the results of the timing relationship between spot and futures indices. They supported that futures tend to move to the leading side of the spot index. They also found that instability in the basis for futures contracts can be explained by the fact that these broadly based contracts seem to have an intrinsic volatility. Furthermore, according to Abhyankar (1995) there is a vast contemporaneous relationship between the FTSE-100 index futures and spot markets. This study has revealed a strong evidence that futures market seems to lead the cash market during periods of ''moderate'' news and when high volatility exists. These results are credible given that lower transaction and entry costs in the stock index futures market may lead traders with market wide information choosing to use futures market. In periods of ''good'' or ''bad'' news, however, no market seems to lead the other one, and this also happens during times of low volatility. Another study is that of Koutmos and Tucker (1996) who modelled the joint distribution of stock index returns and futures index stock returns. Particularly, the results of the study showed that daily volatility in both markets is highly steady on the basis of past innovations and that bad news increase volatility more than good news.

In addition, Lafuente-Luengo (2009), using intraday data from S&P 500 spot index and stock index futures market, investigated the price discovery process in the S&P 500 stock index by examining the intraday lead-lag relationship among market volatilities. This study concluded that futures market act as a leader in incorporation of the arrival of new information. Finally, his results specified that there is a unidirectional causal relationship from futures volatility to cash volatility. From the other side, another prior study examined the dynamics of the relationship between spot and futures markets using Markov-switching vector error correction model for U.S. S&P500, U.K. FTSE100, German DAX, Brazilian BOVESPA and Hungarian BSI (Li, 2009). He concluded that the futures market is not so informationally efficient like cash market especially under the conditions of high variance state.

Lastly, Tse and Chan (2010) examined the lead-lag interaction between the futures and cash markets of the S&P 500 using a threshold regression model. They showed that the restrictions of short selling in the cash market reduce the role of the spot market to lead the futures market. They also concluded that the lead effect of the spot market over the futures market is weaker when there is more market-wide information.

The existing literature is ambiguous as to whether futures markets help cash markets reduce their volatility and price more efficently. There are two theories in the literature about the relationship between futures markets and underlying cash markets. One theory supports the argument that the reduction of spot market volatility and the

simultaneous broadening of market depth are the aftermath of the introduction of stock index futures. The other theory supports that futures markets might distort cash market prices by increasing volatility.
Danthine (1978) claimed that futures markets improve market depth and reduce volatility. In the same line, Morgan (1999) suggested that the introduction of futures markets have a stablilising effect on the underlying cash market price volatility. The price discovery along with the rational decisions taking by traders lead to the establishment of conditions for more efficient spot market pricing. Furthermore, Board et al. (2001) argued that there was no evidence that futures trading destabilises the spot morket. By applying a stochastic volatility model to the UK, they found that there was also no evidence that an increase in volume in one market relative to the other destabilises the cash market. According to Illueca and Lafuente (2003) revealed no evidence to support the hypothesis of transmission of volatility from futures to Spanish stock market volatility. They also disagreed with assumption that futures trading tends to destabilize cash market prices in Spanish financial market. Last but not least, Bohl et al. (2011) investigated the impact of introduction of index futures trading in Poland on the stock market volatility. By applying a Markov-switching-GARCH approach, they concluded that the introduction of index futures trading in Poland does not seem to increase volatility of the underlying stock market. They confirmed that index futures trading does not influence cash market volatility and they rejected the argument of destabilization hypothesis.
On the other hand, the other current of literature presents arguments in favour of the idea that futures trading destabilizes the underlying cash market by increasing its volatility mainly due to the presence of uninformed traders. To this conclusion arrived Finglewski (1981) stating that a lower level of information of futures traders results in increased cash market volatility. The aforementioned view of destablizing impact of derivatives trading is also based on the fact that futures are characterized by high leverage and that a narrowly defined deliverable commodity could attract uninformed traders to the market who trade on the basis of noise rather than information. According to Gullen and Mayhew (2000) found that the conditional volatility has increased since the introduction of futures markets in United States and Japan.

3.3.2 Carrying-Cost Model for an Equity Index

The relationship between futures and spot prices can be defined by the cost of carry model which determines the arbitrage-free price of a futures contract. This states that the futures price is determined by the cost of financing an asset with deferred delivery in futures market in comparison to buy the asset in the spot market and carrying it. In the case of stock index, the stocks can be bought in the spot market instantly or a position to be held on a stock index futures contract with deferred settlement. Thus, the net carrying cost advantage of delivering stocks later on is equal to the difference between the annual risk-free rate and the dividend yield. The spot-futures parity theorem describes the theoretically fair relationship between spot and futures prices and is expressed as:

$$F_o = S_o(1 + r_f - d) \tag{3.5}$$

Where (F_o) is the futures price, (S_o) is the spot price, (d) is the dividend yield of stock and (r_f) represents the annual risk-free rate.
The violation of the parity relationship that states that the theoretical correct price of an index futures contract should be equal to the spot index price plus the cost of carrying the index for the duration of contract, would give rise to arbitrage opportunities. If this condition does not hold, the arbitrage opportunities will exist by taking a position in the cash market and an opposite one in the futures market. The price of stock index

futures and spot price cannot be expected to trade at the same level prior to expiration. The difference between the futures and spot prices is referred to as the basis. This basis reflects the ''cost of carry'' considerations and it should be equal to the cost of carry of the underlying.

Negative carry prevails when stock index futures tend to price at higher levels than the underlying spot index price and the basis increases (positive number- futures less spot) (Hull, 2002).On the other hand, when stock index futures tend to decrease compared to spot index price, the dividends exceed the financing costs of underlying index, the basis is a negative number and positive carry prevails. At the expiration of the futures contract the basis should be zero since spot index value is on the same level with the futures price on the final settlement date of futures contract. This process is known as convergence of spot and futures prices as the delivery date approaches.

The futures market prices do not exactly equal theoretical (fair) prices, mainly due to features like market efficiency and liquidity (Ruttiens, 2013). The theoretical basis can differ from market basis depending on market conditions. Furthermore, the theoretical basis is also called carry basis, and the difference between the (gross) basis and the carry basis is called net basis. Any deviation of futures price from its theoretical (fair) value can be soon eradicated by arbitrage activities. Index arbitrage opportunities are calculated using computerized real-time high frequency data which refers to as program trading. The program trading was a subject of controversy, especially after the 1987 crash, since it was blamed for causing extreme volatility that contributed to significant market crises. According to Stoll and Whaley (1986) volatility on the stock market is higher on the expiration day of futures contracts than on the average of other days and the volume is substantially greater than normal in the last hour of trading. This resulted in the NYSE imposing higher margins on futures trading along with launching rules which prevent program trading during certain times in order to decrease volatility. In reality it is not always so easy to implement arbitrage activities since transaction costs (commissions, fees, and bid-offer spreads) exist that follow entering arbitrage positions. Nowadays, the complex algorithms are executed by automated trading robots using very high-frequency data that causes an excess volatility in cash market.

3.4 Financial Market Volatility

3.4.1 The Causes of Volatility

Some researchers have claimed that there is a relation between market and macroeconomic variables. It is widely accepted that stock market volatility does increase during recessions. Others have claimed that volatility seems to have a relation with trading activity. During the last decades many studies have argued that volatility is not constant over time. The rate of arrival of information is born on the volatility of the value of an asset (Fischer, 1986). It is possible that the volatility of a traded asset is not the same when the exchange is open as when it is closed. The relevant unit of time for the generation of information affecting the prices is the chronological day. Fama (1965) found that the variance of the weekend and holiday changes was not three times, but only 22% higher, the variance of the day-to-day changes within the week. These results turn out the volatility is far greater when the exchange is open than when it is closed.

3.4.2 Volatility Models

It is widely known that there is an abundance of risks in financial markets especially in times of turbulence. The framework that has to be at the heart of finance, is to study which risk has to be taken and how much it is expected to be compensated for taking them. The implausible amount of news propagation is connected with periods of high volatility. Furthermore, unstable or deteriorating macroeconomic circumstances result in bigger financial market volatility (Schwartz, et al., 2011). According to Mandelbrot and Taylor (1967), the variation of volatility can be associated with arrivals of information. Financial theories are often based on assumptions regarding the structure of price data (Andreou, et al., 2001). For instance, the empirical research on Efficient Market Hypothesis (EMH) has been assumed that security prices at any point in time fully reflect particular subsets of available information. The efficient markets model were phrased in terms of random walk (Fama, 1970). The assumption that the conditions of market equilibrium can be relied on the terms of expected returns is the basis of ''fair game'' efficient markets models. The Black-Scholes model assume that the returns follow a normal distribution. Financial time series exhibit periods of time where the volatility is persistently low and alternate with periods of persistently high volatility. Referring to an asset return as a collection of random variables over a period of time, consist a time series. The dynamic structure of linear time series helps the analysis of the theories of stationarity, autocorrelation function, modeling and forecasting. The objective here is to understand the distributional properties of daily stock returns. Empirical evidence of time series of daily stock consist of leptokyrtic distribution, a distribution with heavy tails, relative to normal distribution, which tends to contain some extreme values in the tails, skewness and volatility clustering (large movements are followed by the same large movements, while small movements are expected to follow small returns) (Floros, 2009). According to theory, the expected present value of the asset's future income flows should be equal to the price of this asset. But as time passes, new information is released which alters the expectations. This can give an explanation why returns are random and volatility fluctuates over time especially in periods of crisis when markets plunge due to flood of bad news. Thus, volatility clustering is an outcome of clusters of arrivals of various types of news.

However, this explanation is not so easy to examine empirically since the contents of any type of news must be measured.

Measuring volatility is not simple and instantaneous volatility is unobservable that needs time to reveal itself. In order to get a true result and to be close to the true volatility, the problem of the large sampling error has to be addressed by using the appropriate estimator (Sinclair, 2008). Generally, volatility is widely accepted as a time-varying variable. Additionally, it is widely common to confuse volatility with risk. Price fluctuations are bound to happen in markets, as a result volatility is inevitable. But when a stock is risky, it means that it can lead to losses.

Volatility estimation is of central importance to risk management and number of attempts have been made the last 50 years to ameliorate volatility measures. Further, volatility modelling has received a lot of attention in the literature mainly because of the 2008 financial crisis. It has to be pointed out that there are various statistical estimators in order to measure volatility. Many of these estimators use information on daily trading ranges. Typically in financial theory volatility refers to an asset's degree of unpredictable price change over specific period of time, and contains an element of uncertainty. Looking at the basic volatility estimators, five major types of volatility measures are listed as following:

Historical volatility measure refers to the volatility of a financial asset over a specified period of the past through the price process (Degiannakis & Floros, 2015). In terms of mathematics, historic volatility is the annualized standard deviation of daily returns over a specific period of time. Considering a sequence of known historic daily close prices from cash market $S_1,\ldots,S_N$, the return from day n to day n+1 is calculated as $R_n = \ln(\frac{S_{n+1}}{S_n})$ and $\bar{R}$ the mean return, the historic volatility would be the annualized standard deviation of the returns, supposing that there are 252 business-trading days and N is the number of observations, that equals to $\sigma_{hist.} = \sqrt{\frac{252}{N-1}\sum_{n=0}^{N-1}(R_n - \bar{R})^2}$.

Realized volatility refers to the volatility that is directly measured under a general semi-martingale model setting, using high frequency data from intraday observations (Andersen & Bollerslev, 1998 ; Zhang, et al., 2005). A fundamental point in modelling realized volatility is the information released during non-trading hours in global financial markets (Ahoniemi & Lanne, 2013). The widespread availability of databases providing the intradaily prices of financial assets gave the opportunity to researchers to use data sampled at a high frequency in order to compute ex-post measures of volatility (Bauwens, et al., 2012). A number of authors, including Bolleslev, Shephard and Andersen, used the method known as realized volatility approach.

Implied volatility is that value of the volatility of the underlying asset which comes from the observed option prices of this asset, based on a theoretical option pricing model (Black-Scholes-Merton model) and explains the current market price of an option. The implied volatility of futures options is important information in order to follow the optimum strategy plan since implied volatility changes having effect on the results of trading strategies. Implied volatilities are used to monitor the market's opinion about the volatility of an actively traded financial asset.

The stochastic volatility refers to the fact that the volatility of the underlying asset is not constant but it is itself randomly distributed. In other words, stochastic volatility models treat price volatility as a random variable.

The conditional volatility is that value of the volatility which is conditional on the available information set (Degiannakis & Floros, 2015). The Autoregressive Conditional Heteroscedasticity (ARCH) model is based on the return series of a financial asset and allows the variance to change through time. Finally, stochastic volatility (SV) models are more appropriate to represent the behavior of the returns in real financial markets (Pederzoli, 2006).

3.4.3 Basics of Stochastic Calculus

General Wiener processes are widely used as a special stochastic process with zero drift and variance proportional to the length of the time interval in order to describe the behavior of financial products. This means that the rate of change in expected value is zero and the rate of change in variance is one (Tsay, 2010). In practice, the modelling of the returns, which are more stable over time than long time series with large prices fluctuations, is implemented by a general Wiener process. The generalized Wiener process in which the expectation has a drift rate μ and the rate of variance change σ^2. Then, for a random variable X and combining a deterministic process with a Wiener process in dZ : $dX(t) = \mu dt + \sigma dZ(t)$ (3.7)
Where drift rate and volatility are constant.
In a continuous series of (spot) prices S, instantaneous return equals:

$$X(t) = \frac{dS(t)}{S(t)} \qquad (3.8)$$

From (3.7) and (3.8), $dS(t) = \mu S(t)dt + \sigma S(t)dZ$ (3.9)

CHAPTER 4
UK & US Derivative Markets

The 2008 stock market crash in the United States ranks as the second worst drop in terms of percentage drop since the Great Depression of the 1930s. From the peak of 13,930 in October 2007 to a low of 6,544 in Februrary 2009, the Dow Jones average took a dive of 53 percent. Previously, the largest bankruptcy filing in the history of the United States took place on September 15, 2008. Lehman Brothers Holdings Inc. filed for bankruptcy protection having as a consequence the plummeting of global markets. In March 2007, the first visible signs of an increase in default of homeowners, followed in the end of 2007 by the realization by the financial community that the problem would be much more severe. In very simple terms, the 2008 market crash was as a result of defaults on consolidated mortgage-backed securities. During the previous years the proliferation of financial instruments that promote irresponsible borrowing was vast. Therefore an uncontrollable speculation on real estate prices along with the simultaneous defaults and rising interest rates led to a real estate bubble to burst.

Financial crises have always been on the center of investors', researchers' and policy makers' attention. Amid financial crisis of 2008, the derivatives market were frequently misunderstood. The derivatives attracted enormous attention and have been the target of widespread criticism. Advances and innovations in financial technology have provided benefits and broad access to capital for buyers and great opportunities for higher yields for investors. The transformation of mortgages, written by the lending commercial banks, into investable (mortgage-linked) securities like CDOs (Collateralized Debt Obligations) and their derivatives, like CDO squared structures attracted a lot of individual investors, banks, pension funds, as well as hedge funds and other countries. However, the inadequacy of effective regulations contributed to abuse of mortgage-linked securities and their derivatives. The growth of the real-estate bubble and of the stock market bubble led to a huge extraction of wealth that increased the demand. Furthermore, the development of an unregulated over-the-counter (OTC) derivatives market was another contributing factor that resulted in the 2008 market crises. The unregulated use of credit derivatives such as CDS (Credit Default Swaps) was a major part of the development of the 2008 market crises. Last but not least, it has to be pointed out that according to the Bank of International Settlements (BIS), the total notional amount of credit default swaps was $57.9 trillion in December 2007, which was 2,895 times higher than the gross market value of those swaps reflecting the enormous growth of the market the last decade (Peery, 2011). Following the 2008 financial crisis, derivatives were the subject of a historic reform.

In the aftermath of the global financial crisis, the demand for risk in financial markets declined, as investors aimed to rebalance their portfolios and to hedge their risky positions in cash markets by opening the offsetting positions in futures markets.

During periods of domination of bad news in either market may increase volatility in both markets.The relation between spot and futures markets is dominated by the volatility spillover hypothesis and there is a possibility assymetries in volatility to spill over from spot to futures or vice-versa (Tao & Green, 2012). They studied volatility asymmetries in the FTSE100 stock index and index futures markets and the linkages between the markets using DCC-TGARCH-M analysis. The data covered the period from October 28, 1986 through December 30, 2005 including the move to electroning trading by the London International Financial Futures Exchange (LIFFE) on 30/11/1998. Moreover, according to the empirical results of the study, it could be mentioned that there is a strong evidence of asymmetry in the conditional variance in both markets, the negative information shocks have a larger effect on the conditional

variance than do positive shocks. Finally, they suggested that the variance shocks originate separately in each market.
The years following the global financial crisis in 2008 have provided much evidence to contend that financial crisis is still ongoing and many changes took place over this period till 2013, such as Eurozone debt crisis. In their survey Antonakakis et al. (2016), using a dynamic volatility spillover mechanism to examine dynamic spillover effects between UK and US spot and futures markets within a generalized VAR framework. The dataset covered the period from February 25, 2008 to March 14, 2013 from S&P 500 (US) and FTSE 100 (UK) markets that includes 1247 trading days. The empirical outcomes of their study supported that spot and futures volatilities in the UK are net receivers of spillovers to volume of futures trading. They found evidence of bidirectional interdependence between spot and futures volatilities in the UK and the US, and that volume of futures trading has a greater forecasting ability than open interest. Lastly, the empirical findings of their study agreed that trading volume that reflects market liquidity is more important than open interest for futures markets in order to improve the ability of traders to forecast futures prices.
For the UK and US markets, Karunanayake et al. (2010) investigated the interaction between financial markets and their volatility, focusing on global financial crisis of 2008-2009. They could not be found any positive significant influence on the mean returns in markets resulting from the global financial crisis. However, they supported that the 2008 global financial crisis has contributed to the increased stock return volatilities and that the positive return spillovers effects are unidirectional from both the UK and US markets to the small markets of Australia and Singapore.
For UK market pre-crisis period, Areal and Taylor (2002) calculated FTSE-100 index futures volatility measured at the daily frequency. The FTSE-100 index futures was more volatile when the market opened, when American markets were opened and when macroeconomic news were released in the US and the UK.
For US market, Dawson and Staikouras (2009) investigated whether the volatility derivatives trading had decreased the volatility of the cash market index by using conditional volatility estimators. The data covered the period from January 3, 2000 to May 30, 2008 from S&P500. Moreover, the introduction of volatility derivatives had altered the way that the unexpected shocks were absorbed. In comparison with U.K. equity index (FTSE-100), the shocks were easily absorbed and quickly dissapeared in the post-event date era in US equity index. Their empirical findings argued that the UK equity index suffered from the persistence of shocks to volatility.
In their study, Ferris et al. (2002), by using vector autoregressive approach, claimed that increased volatility lowered pricing error in the S&P 500 index futures market. According to the survey, as market volatility increases, investors sell off their future positions with larger declines in futures prices.
Additionally, Huang (2012) investigated volatility transmission process between the US (S&P 500 futures), the UK (FTSE100 index futures) and Japanese (Nikkei 225) stock index futures markets. Their sample data included the period from 1 January 1989 to 31 December 2006. Their results supported that there is strong evidence of a bidirectional cross market volatility transmission between the UK and the US. According to Yarovaya et al. (2016) volatility spillovers from the US is higher than that from the UK in futures markets.

CHAPTER 5
Methodology

5.1 Estimation of Volatility

The volatility can be computed ex-post from data of various frequencies. A trading session of an exchange trading day can be influenced by a number of local phenomena, which are not obvious when using a series of close prices on a daily basis, in particular a type of boundaries condition. This has led to several measures of an intraday volatility estimator taking into account an open and close price of the session and high and low prices that are highest and lowest prices quoted during the session respectively (Ruttiens, 2013).
Let s(t) be the price of the asset at time t and s(t) is generated by the process of

$$ds(t) = as(t)dt + \sigma s(t)dW(t) \tag{5.1}$$

where a and σ are assumed constants for the moment, and W(t) is a standard Brownian motion (Rogers, et al., 1994). The equation (?.?) is based on the hypothesis that the continuous-time geometric Brownian motion is followed during periods between transactions that prices cannot be observed. It is well known that the solution of Equation (3.8) has a logarithmic form

$$ln\left(\frac{s(t)}{s(t-1)}\right) = (a - 0.5\sigma^2) + \sigma\big(W(t) - W(t-1)\big) \tag{5.2}$$

$$\ln\big(s(t)\big) = \ln\big(s(t-1)\big) + (a - 0.5\sigma^2) + \varepsilon(t) \tag{5.3}$$

From equation (5.3) ln(s(t)) follows a random walk with drift and errors are independent and identically distributed.

$$\varepsilon(t) = \sigma\big(W(t) - W(t-1)\big) \sim N(0, \sigma^2) \tag{5.4}$$

5.2 Range-Based Estimators of Volatility

In statistical terminology, the standard definition of volatility it is the square root of the variance,

$$\sigma^2 = \frac{1}{N-1}\sum_{\iota=1}^{N}(x_i - \mu) \qquad (5.5)$$

where (x_i) is the return of day (*i*), and (μ) is the average return over the N-day period.
In finance it is not easy to distinguish mean returns (drift) from variance since mean returns are extremely noisy and for normal distributions the mean is set to zero. Using more data gets a sample to be less biased.
Consider a trading day period, denoted by {t}. The simplest measure of volatility is defined as the difference between the high and low prices in logarithms:

$$\sigma^2 = \ln\left(\frac{H_t}{L_t}\right) \qquad (5.6)$$

where (H_t) is the high price at day t and (L_t) is the low price.
Another volatility estimator was developed by Parkinson (1980), following a geometric Brownian diffusion process by using only high and low prices and related returns:

$$\sigma^2 = \frac{1}{4ln2}\left(\ln\left(\frac{H_t}{L_t}\right)\right)^2 \qquad (5.7)$$

The Parkinson's estimator could be as much as 8.5 times more efficient than log-squared returns (Chan & Lien, 2003). Both volatility estimators are unbiased when the sample data are repeatedly observed.
Thereafter, the other well-known volatility estimator was developed by Garman and Klass (1980), providing an estimator with superior efficiency, which was based on the combination of high, low, opening and closing prices. It is

$$\sigma^2 = \frac{1}{2}\left(\ln\left(\frac{H_t}{L_t}\right)\right)^2 - (2ln2 - 1)\left(\ln\left(\frac{C_t}{O_t}\right)\right)^2 \qquad (5.8)$$

where (C_t) is the closing price at day t and (O_t) is the low price. The Parkinson and ''Garman and Klass'' estimators are based on a geometric Wiener process in prices and are valid only for processes with zero-drift.
Previous studies assume that the underlying follows a driftless geometric Brownian motion, cannot be applied when the drift term is not zero.
Hence, an alternative approach that is more generally applicable, and has substantially lower sampling error, was proposed by Rogers, Satchell (1991) and Rogers, Satchell and Yoon (1994). They introduce a volatility measure that outperforms the others when a nonzero drift term exists:

$$\sigma^2 = \left(\ln\left(\frac{H_t}{O_t}\right)\right)\left(\ln\left(\frac{H_t}{C_t}\right)\right) + \left(\ln\left(\frac{L_t}{O_t}\right)\right)\left(\ln\left(\frac{L_t}{C_t}\right)\right) \qquad (5.9)$$

Brandt and Kinlay (2005) show that this volatility measure is downward biased. Further, the correlations between the volatility measures are shown in Table {5.1}, where the data was sampled for a 25-day period and volatility was stochastic with a mean of 14 percent and a drift of 8 percent. Finally, the overall conclusion that is needed to be drawn is that there is no indication that proves and concludes to the best volatility measure.

Correlation	Realized	StDev	Parkinson	Garman-Klass	Rogers-Satchell
Realized	1.00	0.58	0.84	0.85	0.80
StDev		1.00	0.70	0.69	0.39
Parkinson			1.00	0.77	0.74
Garman-Klass				1.00	0.81
Rogers-Satchell					1.00

Table {5.1}: Correlations between the Volatility Estimators for Simulated Data.
Source: M. W. Brandt and J. Kinlay, ''Estimating Historical Volatility'', *''Investment Analytics,* 2005.

5.3 Construction of Daily Return & Monthly Effect

To analyze the monthly seasonality in stock market indices and futures market indices, in this thesis, the concept of monthly market return is utilized. The monthly market return for spot prices and stock index futures prices at day (t) is calculated as follows:

$$\Delta S_t = \ln(\frac{S_{i,t}}{S_{i,t-1}}) \tag{5.10}$$

$$\Delta F_t = \ln(\frac{F_{i,t}}{F_{i,t-1}}) \tag{5.11}$$

where $S_{i,t}$ represents the spot price of cash market index (i) on the trading day of t, similarly $F_{i,t}$ represents the futures price of stock index futures (i) on the trading day t, while $S_{i,t-1}$ is the spot price of cash market index (i) on the trading day (t-1) and $F_{i,t-1}$ is the futures price of stock index futures (i) on the trading day (t-1).

The model of monthly effect has also used by Floros (2008) and is described by Guletkin and Guletkin (1983):

$$\Delta S_t = \sum_1^{12} a_i D_{it} + \varepsilon_t \tag{5.12}$$

$$\Delta F_t = \sum_1^{12} a_i' D_{it} + \varepsilon_t' \tag{5.13}$$

where D_{it} takes the value 1 if the return at time t belongs to month I, and 0 if it belongs to any other month, a_i is the mean return of stock index in month I, a_i' is the mean return of stock index futures in month I, and ε_t (ε_t' for futures) and is an error term assumed to be independent and identically distributed.

The null hypothesis to be tested is H_o=a_1=a_2=…=a_{12} .

The test of a January effect is a test of significance of the estimated coefficient a_1 in a second regression of the form:

$$\Delta S_t = a_0 + a_1 D_1 + \varepsilon_t \tag{5.14}$$

$$\Delta F_t = a_o' + a_1' D_1 + \varepsilon_t' \tag{5.15}$$

CHAPTER 6
Data Description

The data employed in this dissertation comprise 3330 daily observations on the FTSE-100 stock index, 3333 daily observations on FTSE-100 Index Future, 3313 observations on NASDAQ-100 spot index and 3323 observations on E-mini NASDAQ-100 Index Future. Daily closing, opening, high and low prices for the aforementioned spot and futures indices from US (FTSE-100) and UK (NASDAQ-100) are used over the period of 3 January 2006 to 4 March 2019 to calculate volatility and investigate the January effect. Closing, open, high and low prices for stock indices and futures indices were obtained from Thomson Reuters Eikon.

The Financial Times Stock Exchange 100 Index is an index of 100 largest, blue chip UK companies listed on the London Stock Exchange with the highest market capitalization. The NASDAQ-100 is a market-capitalization weighted index of 100 largest non-financial US companies listed on the Nasdaq stock market. The standard FTSE-100 futures contract size is 10 Great Britain pounds per index point of the underlying, while the standard E-mini NASDAQ-100 futures contract size is 20 US dollars per index point of NASDAQ-100.

Table {6.1} gives the descriptive statistics for daily spot and futures prices. They are presented three statistics, which are calculated using the observations in the full sample, skewness, kurtosis and Jarque-Bera. A distribution which presents an asymmetric tail extending toward more positive values, corresponds to a positive skewness feature. Negative skewness indicates a distribution with a dissymetry in tail extending toward more negative values. From the other side, when a distribution presents fatter tails along with more or less peaked than a normal distribution, it has a kurtosis feature. Positive kurtosis indicates a relatively peaked distribution while negative kurtosis a relatively flat distribution in comparison to a normal distribution (Szylar, 2014).

All US series (futures and spot indices) have positive skewness implying that the distribution has a long right tail. From the other side all UK series (futures and spot indices) show negative skewness meaning that the distribution has a long left tail. The values for kurtosis are positive and less than three in UK spot and futures indices indicating that the distributions have heavier tails and a sharper peak than the normal distribution. As for US spot and futures indices, the values of kurtosis are negative imlying that the distributions are not peaked relative to normal having lighter tails and a flatter peak than normal. Furthermore, the Jarque-Bera test rejects normality at the 5% level for all distributions.Hence, the sample of US and UK spot and futures indices has platykurtic distribution.

FTSE100-Index-Future	CLOSE	HIGH	LOW	OPEN
Mean	6153.4851	6196.2994	6108.0868	6154.4252
Median	6196.2500	6239.0000	6146.0000	6197.0000
Std. Deviation	837.9937	828.5024	847.0305	836.8435
Kurtosis	0.2073	0.1722	0.2238	0.1957
Skewness	-0.5172	-0.4972	-0.5319	-0.5122
Minimum	3509.0000	3551.0000	3443.0000	3513.0000
Maximum	7879.5000	7885.5000	7829.0000	7846.5000
Jarque-Bera	1229.9169	1245.9407	1225.6719	1235.9766
Observations	3328	3328	3328	3328
FTSE100-Index	**CLOSE**	**HIGH**	**LOW**	**OPEN**
Mean	6173.1813	6212.8159	6131.6793	6172.7286
Median	6198.5900	6240.1000	6156.2300	6198.1000
Std. Deviation	842.8025	835.1826	851.2655	842.6898
Kurtosis	0.1605	0.1477	0.1755	0.1606
Skewness	-0.4887	-0.4778	-0.4983	-0.4878
Minimum	3512.0900	3564.7500	3460.7100	3512.0900
Maximum	7877.4500	7903.5000	7854.5800	7877.4500
Jarque-Bera	1250.8978	1255.1460	1244.3724	1250.2737
Observations	3329	3329	3329	3329
E-MINI100-NASDAQ-Future	**CLOSE**	**HIGH**	**LOW**	**OPEN**
Mean	3364.1472	3388.5791	3335.5044	3362.6966
Median	2700.5000	2721.2500	2675.5000	2700.7500
Std. Deviation	1748.8217	1758.0709	1736.4709	1747.6039
Kurtosis	-0.4730	-0.4610	-0.4834	-0.4709
Skewness	0.8253	0.8317	0.8188	0.8260
Minimum	1037.5000	1084.2500	1015.7500	1041.5000
Maximum	7719.0000	7749.7500	7683.5000	7723.0000
Jarque-Bera	2047.3213	2041.6514	2051.3299	2045.8271
Observations	3323	3323	3323	3323
NASDAQ100-Index	**CLOSE**	**HIGH**	**LOW**	**OPEN**
Mean	3300.6590	3320.5028	3277.9145	3300.1501
Median	2665.8300	2683.2500	2653.4300	2667.3600
Std. Deviation	1728.3312	1736.3100	1719.0862	1728.2559
Kurtosis	-0.4059	-0.3947	-0.4147	-0.4035
Skewness	0.8427	0.8486	0.8377	0.8435
Minimum	1036.5100	1085.5700	1018.8600	1058.8500
Maximum	7660.1800	7700.5570	7628.5440	7673.0010
Jarque-Bera	1993.4650	1988.3790	1997.0533	1991.9267
Observations	3313	3313	3313	3313

Table {6.1}: *Descriptive Statistics (Price)*
NOTE: *PROBABILITY (rejecting the null hypothesis of normality/Jarque-Bera Test), (p-value)=0*

CHAPTER 7
Empirical Results

This chapter descibes the empirical work and results of this dissertation about modelling volatility and January effect on returns and volatility. Firstly, the first section begins with using several models for the calculation of volatility during the entire period 2006-2019 and during the two sub-periods pre-2008 and post-2008. Secondly, the next section investigates the monthly effect in the cash and futures markets returns of the US and UK indices using daily data before and after the crisis of 2008. Lastly,this chapter ends with examining the January effect in volatility in US and UK spot and futures indices.

7.1 Modelling Volatility

7.1.1 Entire Period

This section looks at the empirical results which are related to spot and futures market volatility in order to clarify through the analysis of the statistical outputs whether and to what extent the four models based on the opening, closing, high and low prices provide a satisfying efficiency in the data. The main aim of this section is simply to calculate the volatility during the entire period of 2006-2019 through the four aforementioned volatility measures.
As far as the volatilities of the futures and spot indices are concerned, the four volatility estimators were considered as the most appropriate measures. In particular, the results of applying equations {5.6}-{5.9} are presented in Table {7.1}. From the examination of the below table it becomes clear that in all cases V_S overestimates V_{gk}, V_p and V_{rs}. The normal distribution assumption is rejected for each volatility estimator using the Jarque-Bera statistic.

FTSE100-Index-Future	V_s	V_p	V_{rs}	V_{gk}
Mean	0.01515	0.00013	0.00015	0.00014
Median	0.01215	0.00005	0.00006	0.00006
Std. Deviation	0.01125	0.00031	0.00043	0.00037
Kurtosis	18.52622	89.00947	140.60201	98.78805
Skewness	3.44933	8.33444	10.48049	8.90626
Minimum	0.00241	2.09E-06	0.00000	2.40E-06
Maximum	0.11889	0.00510	0.00855	0.00592
Jarque-Bera	40026.	1064333.	2686483.	1316312.
Observations	3328	3328	3328	3328
FTSE100-Index	V_s	V_p	V_{rs}	V_{gk}
Mean	0.01386	0.00010	0.00009	0.00009
Median	0.01122	4.55E-05	3.84E-05	4.32E-05
Std. Deviation	0.00974	0.00023	0.00022	0.00019
Kurtosis	16.26699	105.63628	207.65270	125.68810
Skewness	3.09353	8.74155	11.89169	9.34598

Minimum	0.00233	1.96E-06	0.00000	1.49E-06
Maximum	0.10753	0.00417	0.00532	0.00372
Jarque-Bera	29724.	1503579.	5887943.	2136352.
Observations	3329	3329	3329	3329
E-MINI100-NASDAQ-Future	**V_s**	**V_p**	**V_{rs}**	**V_{gk}**
Mean	0.01742	0.00017	0.00017	0.00017
Median	0.01421	7.29E-05	7.37E-05	7.71E-05
Std. Deviation	0.01254	0.00037	0.00040	0.00035
Kurtosis	15.32889	97.01996	198.71206	106.43200
Skewness	3.03768	8.37500	10.94576	8.40624
Minimum	0.00053	0.00000	-6.19E-06	0.00000
Maximum	0.12862	0.00597	0.01070	0.00738
Jarque-Bera	26156.	1262783.	5369753.	1520388.
Observations	3323	3323	3323	3323
NASDAQ100-Index	**V_s**	**V_p**	**V_{rs}**	**V_{gk}**
Mean	0.01429	0.00011	0.00011	0.00011
Median	0.01159	4.85E-05	4.67E-05	4.93E-05
Std. Deviation	0.01031	0.00026	0.00030	0.00026
Kurtosis	17.37665	117.55533	279.01844	194.18604
Skewness	3.17595	9.22009	13.89939	11.68121
Minimum	0.00214	1.65E-06	0	2.20E-06
Maximum	0.11410	0.00470	0.00852	0.00620
Jarque-Bera	34101.	1858450.	10623541.	5121056.
Observations	3313	3313	3313	3313

Table {7.1}: *Volatility Estimates (Entire period)*
NOTE: *PROBABILITY (rejecting the null hypothesis of normality/Jarque-Bera Test), (p-value)=0*

Additionally, E-mini NASDAQ-100 Index Future has the highest daily volatility for all the four models between spot and futures UK and US markets. FTSE-100 Index Future has the second highest daily volatility calculated by the four volatility estimators. Hence, both futures indices show an increase in daily volatility compared to spot indices. Moreover, UK spot and futures markets seem to have lower daily volatility than US markets. Table {7.1} shows that the means of the simple, Parkinson, Garman-Klass and Rogers-Satchell volatility estimates are higher in futures markets in comparison with cash markets. The standard deviation of each volatility measure also has higher values in futures markets. The estimates become more positively skewed and have fatter tails in cash markets than in futures markets. Furthermore, the volatility estimators seem to have fatter tails in US cash and futures markets in comparison with UK spot and futures markets. Figures {7.1}-{7.8} display the four volatility estimates for the UK and US spot and futures markets. In each graph, there is an observable change occurring at the switching point, which indicates an abrupt increase of volatility after mid-August of 2007 when Fitch downgraded Country wide Financial Corp to BBB+.

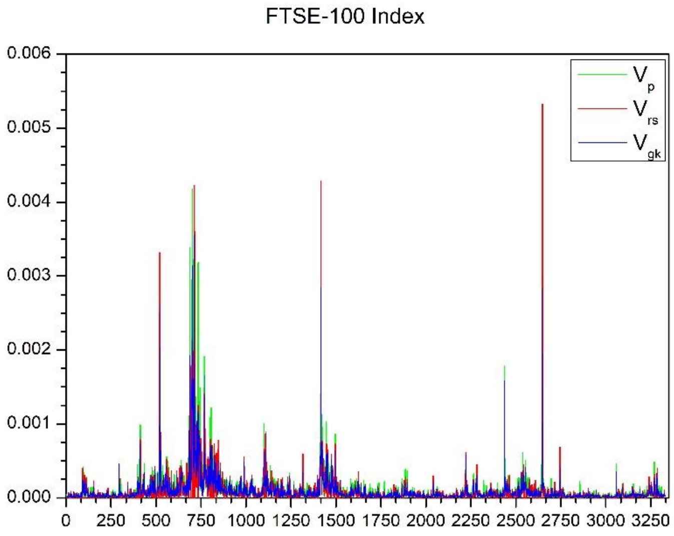

Figure {7.1}: *Volatility Measures V_p, V_{rs}, V_{gk} (FTSE-100 Index).*

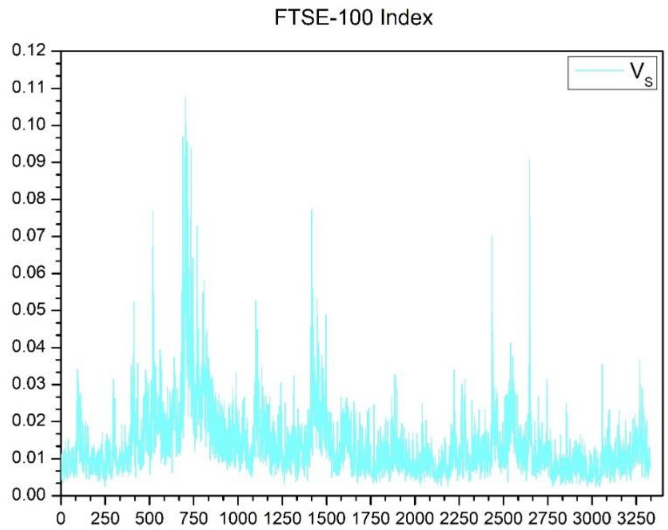

Figure {7.2}: *Volatility Measure V_s (FTSE-100 Index).*

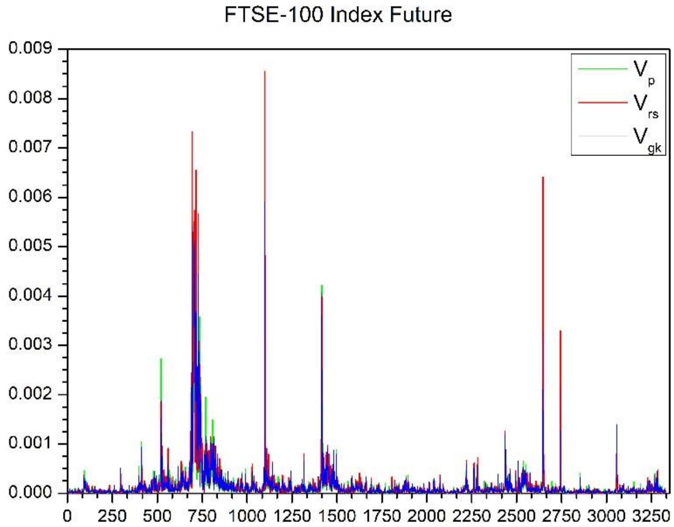

Figure {7.3}: *Volatility Measures V_p, V_{rs}, V_{gk} (FTSE-100 Index Future).*

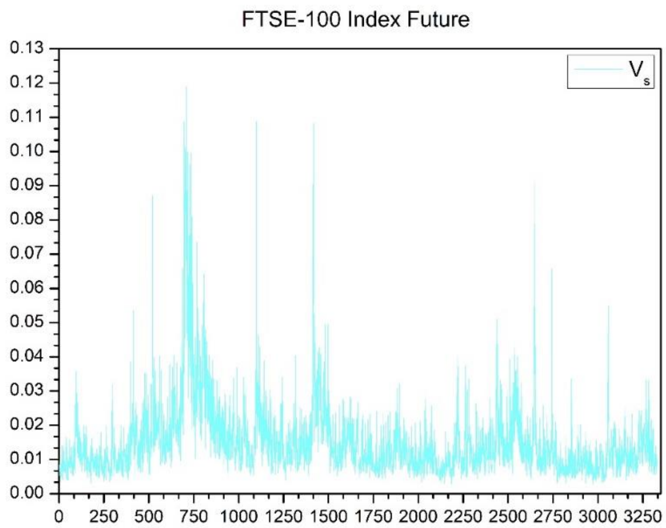

Figure {7.4}: *Volatility Measure V_s (FTSE-100 Index Future).*

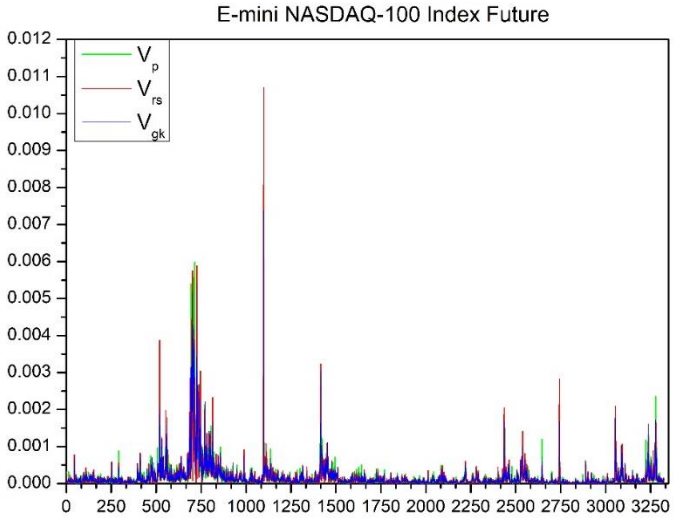

Figure {7.5}: *Volatility Measures V_p, V_{rs}, V_{gk} (E-mini NASDAQ-100 Index Future).*

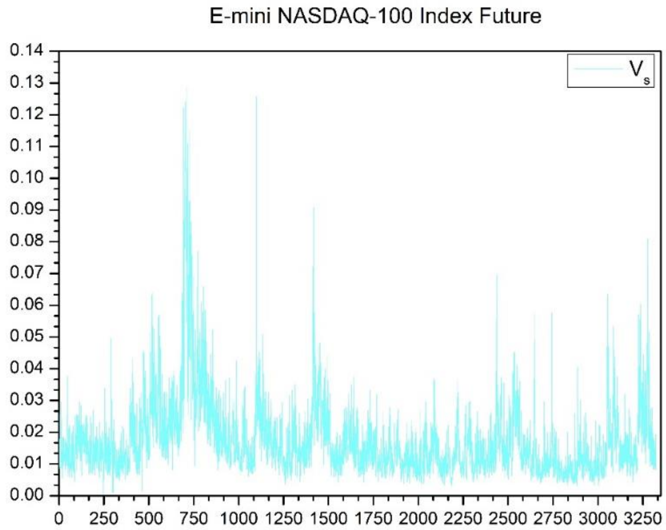

Figure {7.6}: *Volatility Measure V_s (E-mini NASDAQ-100 Index Future).*

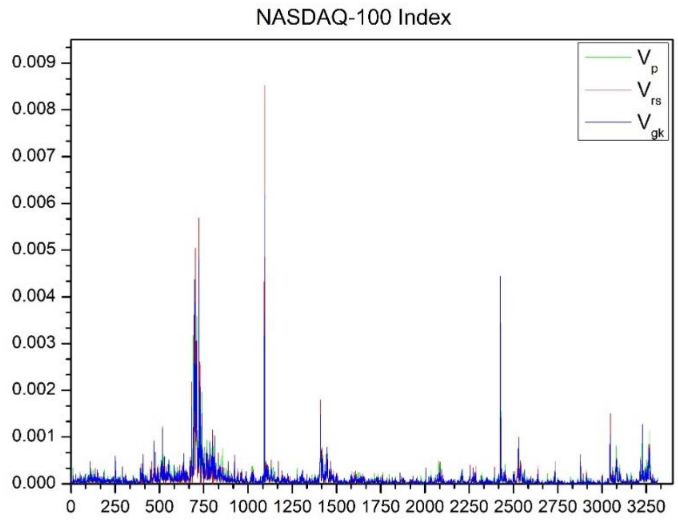

Figure {7.7}: *Volatility Measures V_p, V_{rs}, V_{gk} (NASDAQ-100 Index).*

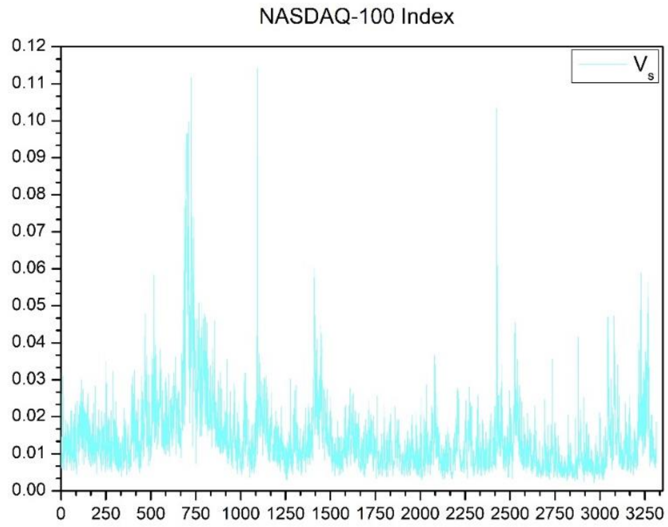

Figure {7.8}: *Volatility Measure V_s (NASDAQ-100 Index).*

Not surprisingly, there are periodic spikes in futures and spot daily volatility, many of which could be associated with macroeconomic events and considering that many changes took place during the years in the sample 2006-2019, such as the global financial crisis, Eurozone debt crisis and ''Brexit''. Two large spikes are far larger than the others. The first occurred on 18/9/2008 in US cash and futures markets, which corresponds to three days after Lehman Brothers filed for Chapter 11 bankruptcy (15/9/2008), and on 19/9/2008 in UK spot and futures markets. The variability of markets was dominant the next period of the height of the global financial crisis, when US market was plummeting, with some smaller but persistent spikes in daily volatility on the mid of October (10/10/2008 & 16/10/2008) and on November 13, 2008 in US

and UK futures and spot indices. It is worth noting that VIX closed at about 87 on November 20, 2008 and simultaneously S&P-500 dropped to an 11 year low following continued signs of economic contraction. The second extreme spike of daily volatility appeared on May 4, 2010 in US cash market and UK futures market, while this spike of realized volatility happened the next day in US futures market during the correction of U.S. stock indices amid continued evidence of a slow economic recovery. This finding proves that futures investors and traders in both the UK and the US markets monitor developments in both the US and the UK. Lastly, two notable spikes occurred on August 24, 2015 in UK and US market, when Brussels task force group charged with handling issues relating to the Brexit referendum in UK and began its work, and on June 24, 2016 which led to a notable shift in UK spot and futures markets since Britain voted to leave the European Union on June 23, 2016.
Figures {7.1}-{7.8} suggest that both daily volatilities for both the NASDAQ-100 and FTSE-100 indices are informative about the variability in the cash and futures markets. Furthermore, the market-wide news is impounded into the NASDAQ-100 and E-Mini NASDAQ-100 simultaneously and this also happens with FTSE-100 spot and futures markets.

7.1.2 Two Sub-periods

Tables {7.2}-{7.5} show summary statistics for the US and UK spot and futures indices with data covering the period from January 2006 to March 2019 over two sub-periods: a ''Pre-2008'' period from January 2006 to 2007-12-31, when Lehman Brothers filed for Chapter 11 bankruptcy protection, and a ''Post-2008'' period from January 2008 to 2019-03-04 , when global financial crisis took place that led to a strong recession in UK and US economies till the end of 2009, while CBOE Volatility Index (VIX) jumped to high levels during the turbulent days in summer and fall 2008 and Eurozone debt crisis took place in the end of 2009. For all distributions of volatility estimators for US and UK cash and stock indices futures markets, the Jarque-Bera test easily rejects the hypothesis that volatility is normally distributed.
From the examination of the below tables it becomes clear that in all cases and sub-periods V_S overestimates V_{gk}, V_p and V_{rs}. Again, in all cases the distributions of volatility estimators are highly positevely skewed. E-mini NASDAQ-100 Index Future has the highest daily volatility for all the four models and sub-periods between spot and futures UK and US markets. FTSE-100 Index Future has the second highest daily volatility calculated by the four volatility estimators. Hence, both futures indices show an increase in daily volatility compared to spot indices. Furthermore, UK spot and futures markets seem to have lower daily volatility than US markets. Tables {7.2}-{7.5} show that the means of the simple, Parkinson, Garman-Klass and Rogers-Satchell volatility estimates are higher during post-2008 period in markets. The standard deviation of each volatility measure also has higher values in futures markets in post-2008 period. The estimates become more positively skewed during post-2008 period compared to the other sub-period. It's worth mentioning that there is convergence between Parkinson, Garman-Klass and Rogers-Satchell volatility estimates, especially in US market, in spot and futures markets. Lastly, during the post-2008 period, the volatility estimators seem to be heavy-tailed in cash market in comparison with future market indicating that financial global crisis tend to lead to the profusion of outliers.

PRE-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.011830	0.000065	0.000052	0.000055
Median	0.010097	0.000037	0.000030	0.000035
Std. Deviation	0.006432	0.000088	0.000070	0.000070
Kurtosis	5.386009	30.040783	29.341959	46.727088
Skewness	1.938743	4.390628	4.226068	5.167548
Minimum	0.002523	0.000002	-0.000001	0.000002
Maximum	0.052255	0.000986	0.000785	0.000907
Jarque-Bera	436.15	17008.28	16103.98	42480.44
Observations	505	505	505	505
POST-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.014218	0.000110	0.000097	0.000098
Median	0.011469	0.000047	0.000040	0.000045
Std. Deviation	0.010183	0.000243	0.000237	0.000209
Kurtosis	15.427393	93.546926	181.997786	110.880698
Skewness	3.046446	8.292189	11.202776	8.837395
Minimum	0.002332	0.000002	0.000000	0.000001
Maximum	0.107531	0.004174	0.005324	0.003722
Jarque-Bera	22540.63	997082.32	3829134.11	1406192.34
Observations	2824	2824	2824	2824

Table {7.2}: *Volatility Estimates for FTSE-100 Index*
NOTE: *PROBABILITY (rejecting the null hypothesis of normality/Jarque-Bera Test), (p-value)=0*

PRE-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.011592	0.000061	0.000061	0.000062
Median	0.009966	0.000036	0.000038	0.000040
Std. Deviation	0.005982	0.000080	0.000073	0.000076
Kurtosis	6.665663	48.924864	26.803098	41.249325
Skewness	1.956912	5.386126	4.056423	4.871121
Minimum	0.003148	0.000004	0.000001	0.000004
Maximum	0.053671	0.001040	0.000801	0.000946
Jarque-Bera	606.25	46913.25	13333.22	32846.19
Observations	506	506	506	506
POST-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.015791	0.000141	0.000165	0.000158
Median	0.012677	0.000058	0.000063	0.000063
Std. Deviation	0.011836	0.000334	0.000467	0.000404
Kurtosis	16.882206	76.860148	120.397659	84.708868
Skewness	3.329613	7.779791	9.724211	8.276643
Minimum	0.002406	0.000002	0.000001	0.000002
Maximum	0.118892	0.005103	0.008550	0.005920
Jarque-Bera	27874.41	669921.87	1665033.07.	817245.36
Observations	2822	2822	2822	2822

Table {7.3}: *Volatility Estimates for FTSE-100 Index Future*
NOTE: *PROBABILITY (rejecting the null hypothesis of normality/Jarque-Bera Test)*

PRE-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.013622	0.000081	0.000079	0.000079
Median	0.012126	0.000053	0.000054	0.000057
Std. Deviation	0.006305	0.000083	0.000092	0.000084
Kurtosis	2.063382	15.797777	22.876318	23.751886
Skewness	1.207667	2.988055	3.952636	3.923836
Minimum	0.003926	0.000006	0.000000	0.000004
Maximum	0.047837	0.000826	0.000918	0.000845
Jarque-Bera	140.38	4172.81	9570.66	10295.74
Observations	502	502	502	502
POST-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.014412	0.000116	0.000114	0.000113
Median	0.011509	0.000048	0.000045	0.000047
Std. Deviation	0.010866	0.000276	0.000325	0.000281
Kurtosis	16.229524	102.442951	243.224231	169.582217
Skewness	3.132837	8.663259	13.053217	10.983940
Minimum	0.002140	0.000002	0.000000	0.000002
Maximum	0.114099	0.004700	0.008523	0.006198
Jarque-Bera	25097.43	1193399.36	6838838.21	330669.11
Observations	2811	2811	2811	2811

Table {7.4}: *Volatility Estimates for NASDAQ-100 Index*
NOTE: *PROBABILITY (rejecting the null hypothesis of normality/Jarque-Bera Test), (p-value)=0*

PRE-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.014958	0.000099	0.000097	0.000099
Median	0.013660	0.000067	0.000067	0.000070
Std. Deviation	0.007087	0.000105	0.000106	0.000102
Kurtosis	2.693966	14.560531	14.944138	13.271152
Skewness	1.291671	3.156664	3.358582	3.123825
Minimum	0.000531	0.000001	-0.000006	0.000001
Maximum	0.049477	0.000884	0.000815	0.000830
Jarque-Bera	142.11	3643.58	3943.44	3035.12
Observations	504	504	504	504
POST-CRISIS	V_s	V_p	V_{rs}	V_{gk}
Mean	0.017864	0.000178	0.000181	0.000179
Median	0.014330	0.000074	0.000075	0.000079
Std. Deviation	0.013236	0.000395	0.000427	0.000381
Kurtosis	13.958301	84.093641	172.773893	92.484263
Skewness	2.941583	7.836484	10.247145	7.871564
Minimum	0.003074	0.000003	0.000002	0.000004
Maximum	0.128625	0.005972	0.010699	0.007380
Jarque-Bera	18170.33	801279.68	3434856.42	969651.36
Observations	2819	2819	2819	2819

Table {7.5}: *Volatility Estimates for E-Mini-NASDAQ-100 Index Future*
NOTE: *PROBABILITY (rejecting the null hypothesis of normality/Jarque-Bera Test)*

7.2 Monthly Effect-Returns

7.2.1 Entire Period

Before examining if the January effect is present, an estimation of the daily return for the US and UK spot and futures indices is implemented. Table {7.6} reports the descriptive statistics of the returns of the FTSE-100 stock index, FTSE-100 Index Future, NASDAQ-100 spot index and E-mini NASDAQ-100 Index Future, and shows the mean, minimum, maximum, standard deviation, skewness, kurtosis, Jarque-Bera statistic and its associated probability value (p-value) for entire period 2006-2019. As shown in Table {7.6}, the mean and kurtosis coefficients for UK and US spot and futures indices are positive, while skewness is negative that means that the series is skewed to the left. Therefore, the UK and US indices show excess kurtosis (i.e. the pdf is leptokyrtic), implying fatter tails than a normal distribution. Due to the presence of excess kurtosis, all the series are non-normal by means of the Jarque-Bera statistics.

	FTSE-100 index	**FTSE-100 index future**	**NASDAQ-100 index**	**E-mini NASDAQ-100 index future**
Mean	2.92E-05	2.94E-05	0.00019	0.00017
Median	0.00015	0.00019	0.00044	0.00042
Std. Deviation	0.00505	0.00505	0.00579	0.00564
Kurtosis	8.03985	7.92849	7.84460	10.75071
Skewness	-0.13888	-0.21933	-0.20423	-0.12891
Minimum	-0.04024	-0.04212	-0.04827	-0.04597
Maximum	0.04076	0.04161	0.05146	0.05593
Jarque-Bera	3531. (0.000)	3393. (0.000)	3261. (0.000)	8299. (0.000)
Observations	3327	3327	3312	3312

Table {7.6}: *Summary Statistics for returns (2006-2019)*
NOTE: *Probability value in parentheses (rejecting the null hypothesis of normality/Jarque-Bera Test)*

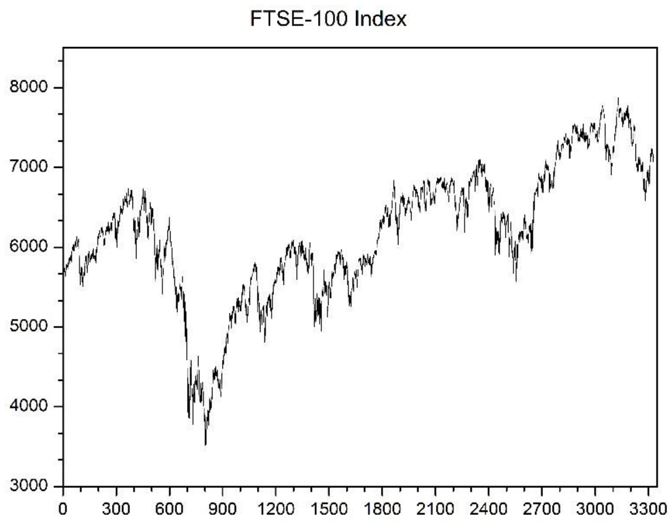

Figure {7.9}: *Graphical plot of FTSE-100 Index price.*

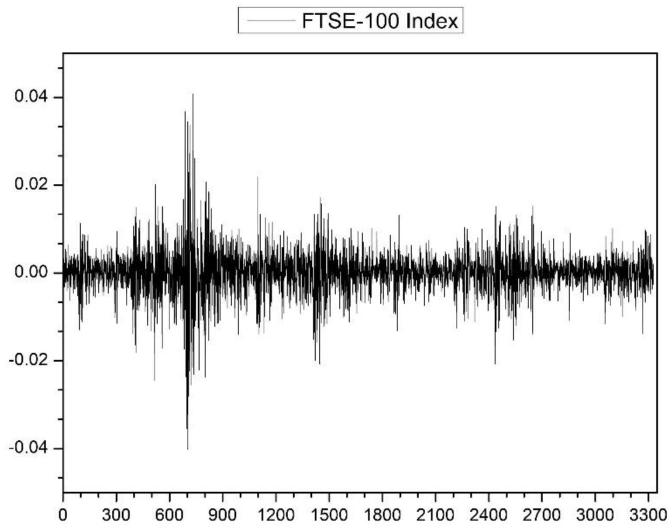

Figure {7.10}: *Graphical plot of FTSE-100 Index return.*

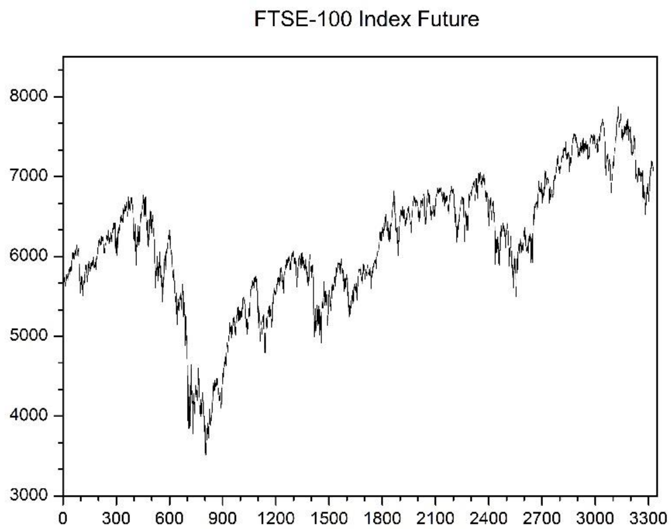

Figure {7.11}: *Graphical plot of FTSE-100 Index Future price.*

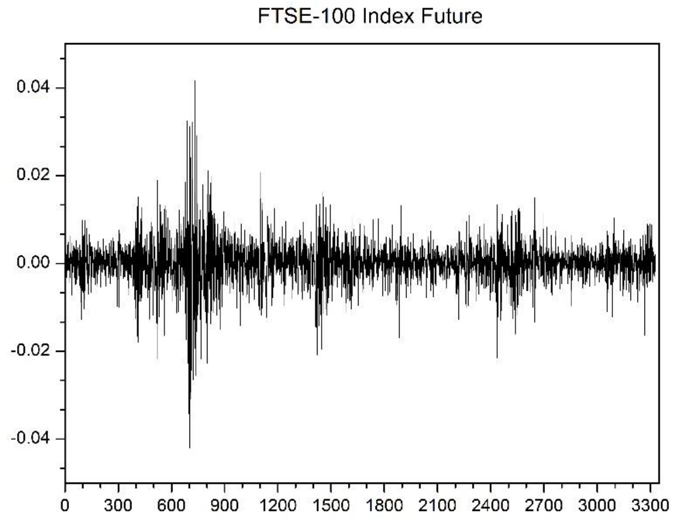

Figure {7.12}: *Graphical plot of FTSE-100 Index Future return.*

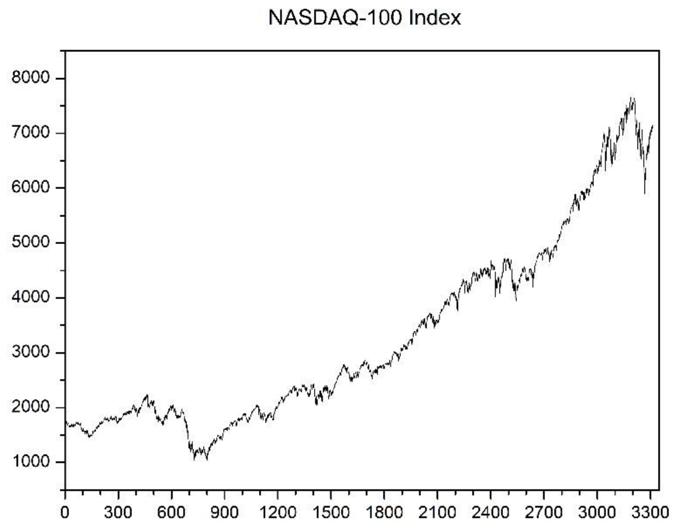

Figure {7.13}: *Graphical plot of NASDAQ-100 Index price.*

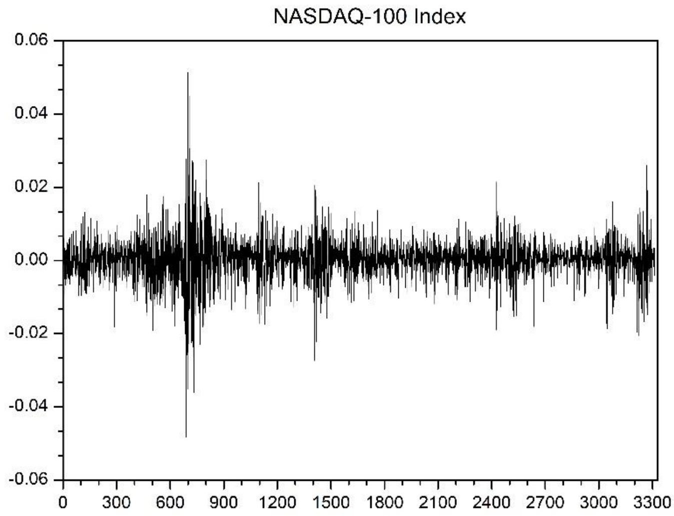

Figure {7.14}: *Graphical plot of NASDAQ-100 Index return.*

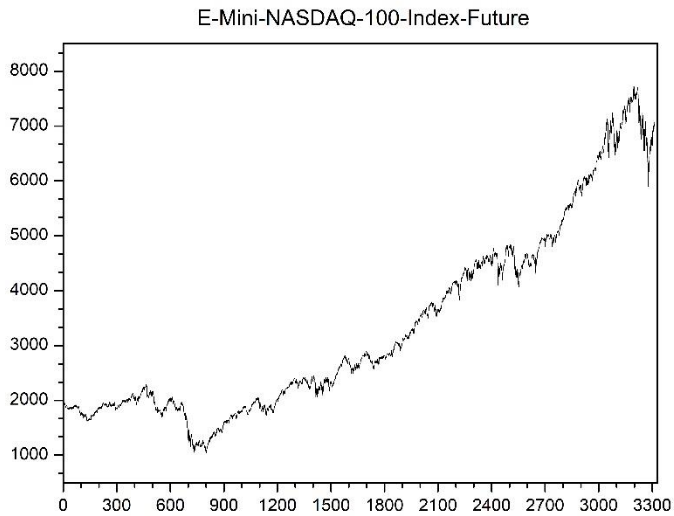

Figure {7.15}: *Graphical plot of E-Mini-NASDAQ-100 Index Future price.*

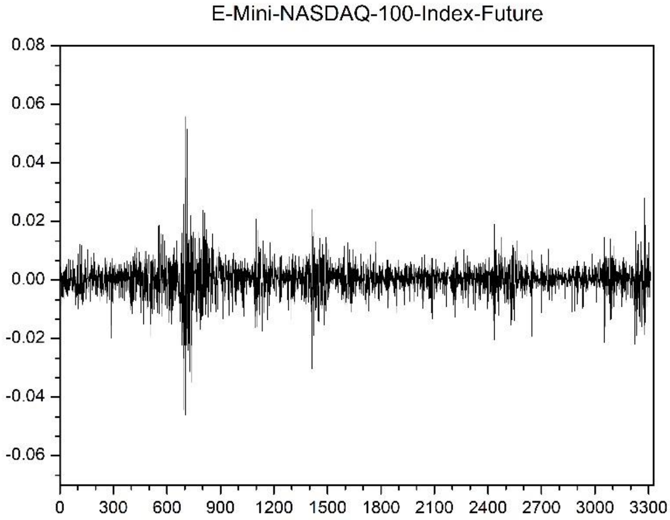

Figure {7.16}: *Graphical plot of E-Mini-NASDAQ-100 Index Future return.*

Additionally, NASDAQ-100 index has the highest mean returns between spot and futures UK and US markets and E-mini NASDAQ-100 Index Future has the second highest mean return. Hence, UK spot and futures markets seem to have lower mean returns than US markets. It is evident that Figures {7.9-7.16}, which are the graphical plots of UK and US spot and futures indices and their returns, depict the above outcomes.

If January effect is present, the positive January returns would be higher than the returns for any other month. The results for the FTSE-100 Index, FTSE-100 Index Future, NASDAQ-100 Index and E-Mini NASDAQ-100 Index Future are presented in Tables {7.7}-{7.10}, respectively.
For FTSE-100 index, the higher returns occur in April and December and lower in June and January and the hypothesis of January effect is rejected. It has to be pointed out that results are not statistically significant for all months using a 95% confidence interval since T-statistics are under 1.96.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	-0.000207	0.000293	-0.705085	0.4808
February	0.000144	0.000300	0.478896	0.6320
March	0.000042	0.000300	0.139722	0.8889
April	0.000489	0.000316	1.547543	0.1218
May	-0.000077	0.000311	-0.247661	0.8044
June	-0.000379	0.000304	-1.248705	0.2119
July	0.000333	0.000298	1.117194	0.2640
August	-0.000142	0.000304	-0.466146	0.6411
September	-0.000120	0.000304	-0.398763	0.6901
October	0.000139	0.000297	0.467970	0.6398

November	-0.000191	0.000302	-0.630830	0.5282
December	0.000377	0.000313	1.202888	0.2291

Table {7.7}: *FTSE-100 Index (regression equation (5.12), method: least squares).*

For FTSE-100 index future, the higher returns occur in April and July and lower in June and January. The lower returns are found to occur in the same months in UK spot and futures markets. It is worth mentioning that returns for all months are not again statistically significant. For the entire period, it is clear that there is no evidence of a monthly effect in UK futures and cash markets.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	-0.000215	0.000293	-0.731064	0.4648
February	0.000213	0.000300	0.711007	0.4771
March	-0.000009	0.000300	-0.031277	0.9750
April	0.000527	0.000316	1.670302	0.0950
May	-0.000037	0.000311	-0.120515	0.9041
June	-0.000436	0.000303	-1.436458	0.1510
July	0.000334	0.000298	1.120139	0.2627
August	-0.000051	0.000304	-0.168297	0.8664
September	-0.000148	0.000303	-0.487646	0.6258
October	0.000128	0.000297	0.430932	0.6665
November	-0.000123	0.000302	-0.407912	0.6834
December	0.000216	0.000314	0.688475	0.4912

Table {7.8}: *FTSE-100 Index Future (regression equation (5.13), method: least squares).*

Table {7.9} details the result of the ordinary least squares model for the full period in US cash market (NASDAQ-100 index). For NASDAQ-100, the results show higher returns in July, April and March and lower in June and November. However, all the p-value of T-tests is statistically insignificant and the hypothesis of January effect is rejected.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000101	0.000345	0.292505	0.7699
February	0.000225	0.000353	0.637064	0.5241
March	0.000434	0.000343	1.265357	0.2058
April	0.000515	0.000354	1.455009	0.1458
May	0.000166	0.000349	0.475680	0.6343
June	-0.000277	0.000347	-0.798767	0.4245
July	0.000618	0.000350	1.765409	0.0776
August	0.000146	0.000341	0.428956	0.6680
September	0.000181	0.000357	0.505942	0.6129
October	0.000196	0.000342	0.571339	0.5678

November	-0.000033	0.000355	-0.093020	0.9259
December	-0.000005	0.000352	-0.014928	0.9881

Table {7.9}: *NASDAQ-100 Index (regression equation (5.12), method: least squares).*

For E-Mini-NASDAQ-100 index future, the results show higher returns in July and April and lower returns in the following months: June, November, December and January. In fact, all the p-values of t-tests are insignificant indicating that there is no significant month of monthly effect during 2006 to 2019 and the hypothesis of January effect is rejected.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000068	0.000335	0.201969	0.8399
February	0.000237	0.000344	0.688051	0.4915
March	0.000418	0.000333	1.253746	0.2100
April	0.000483	0.000342	1.411769	0.1581
May	0.000176	0.000340	0.518308	0.6043
June	-0.000292	0.000338	-0.865411	0.3869
July	0.000595	0.000340	1.753343	0.0796
August	0.000139	0.000332	0.417984	0.6760
September	0.000159	0.000347	0.457499	0.6473
October	0.000160	0.000332	0.482901	0.6292
November	-0.000030	0.000346	-0.087646	0.9302
December	-0.000025	0.000341	-0.074668	0.9405

Table {7.10}: *E-Mini-NASDAQ-100 Index Future (regression equation (5.13), method: least squares).*

Hence, it is noticeable that there is no January effect in US over the entire period (1/2016-3/2019) examined.
Furthermore, the January effect can be examined by a simply test for significance of the estimated coefficient α_1 in regression: $R_t = a_0 + a_1 D_1 + \varepsilon_t$ (1)
The above regression should show significant positive slope coefficient to indicate a January effect. Tables {7.11}-{7.14} present results for US and UK spot and futures indices, respectively. The dummy variable of January (α_1 of D_1) is not significant for all indices, and therefore the hypothesis of unusual large stock and futures returns is rejected. These findings confirm previous results obtained from the other regression equation.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	-0.000053	0.000092	-0.576359	0.5644
a_1	-0.000260	0.000307	-0.845292	0.3980
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.11}: *FTSE-100 Index for the whole period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000053	0.000092	0.581016	0.5613
a_1	-0.000268	0.000307	-0.871525	0.3835
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.12}: *FTSE-100 Index Future for the whole period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000197	0.000105	1.870007	0.0616
a_1	-0.000096	0.000361	-0.265237	0.7908
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.13}: *NASDAQ-100 Index for the whole period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000184	0.000102	1.799615	0.0721
a_1	-0.000116	0.000350	-0.332830	0.7393
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.14}: *E-Mini-NASDAQ-100 Index Future for the whole period.*

7.2.2 Two Sub-periods

Tables {7.15}-{7.18} report the descriptive statistics of the returns of the FTSE-100 stock index, FTSE-100 Index Future, NASDAQ-100 spot index and E-mini NASDAQ-100 Index Future for the two sub-periods: pre-2008 period and post-2008 period. As shown in Tables {7.15}-{7.18}, the kurtosis coefficients for UK and US spot and futures indices are positive, while skewness is negative that means that the series is skewed to the left. Sample of post-2008 period shows the lowest mean daily returns whereas sample of pre-2008 has the highest mean daily returns in UK market. On the contrary, sample of post-2008 period shows higher mean daily returns compared to sample of pre-2008 period in US spot and futures markets. Notably, the descriptive statistics show higher daily mean returns in US market.

It has to be pointed out that the UK and US indices show excess kurtosis (i.e. the pdf is leptokyrtic) during post-2008 period, implying fatter tails than a normal distribution.

However, the descriptive statistics for the other sub-period show that kurtosis of daily returns of UK and US cash and futures indices is less than three which means that daily returns are light-tailed. In all cases the standard deviation of daily returns increases during the post-2008 period. Lastly, during all the sub-periods, the standard deviation of daily returns of US spot and futures markets has higher values compared to UK market.

	Pre-2008	**Post-2008**
Mean	0.000110	0.000015
Median	0.000277	0.000134
Std. Deviation	0.004160	0.005195
Kurtosis	2.036365	8.271520
Skewness	-0.399299	-0.111422
Minimum	-0.018175	-0.040240
Maximum	0.014958	0.040756
Jarque-Bera	32.8933 (0.0000)	3275.6732 (0.0000)
Observations	504	2824

Table {7.15}: *Summary Statistics for returns of the FTSE-100 Index*
NOTE: *Probability value in parentheses (rejecting the null hypothesis of normality/Jarque-Bera Test)*

	Pre-2008	**Post-2008**
Mean	0.000110	0.000015
Median	0.000211	0.000186
Std. Deviation	0.004099	0.005200
Kurtosis	1.984912	8.103737
Skewness	-0.357263	-0.202289
Minimum	-0.017938	-0.042123
Maximum	0.015136	0.041607
Jarque-Bera	32.4242 (0.0000)	3082.0724 (0.0000)
Observations	505	2822

Table {7.16}: *Summary Statistics for returns of the FTSE-100 Index Future*
NOTE: *Probability value in parentheses (rejecting the null hypothesis of normality/Jarque-Bera Test)*

	Pre-2008	**Post-2008**
Mean	0.000187	0.000189
Median	0.000546	0.000424
Std. Deviation	0.004713	0.005967
Kurtosis	0.933248	8.092829
Skewness	-0.190057	-0.203791
Minimum	-0.018069	-0.048271
Maximum	0.018008	0.051461
Jarque-Bera	92.1829 (0.0000)	3057.3170 (0.0000)

Observations	501	2811

Table {7.17}: *Summary Statistics for returns of the NASDAQ-100 Index*
NOTE: *Probability value in parentheses (rejecting the null hypothesis of normality/Jarque-Bera Test)*

	Pre-2008	**Post-2008**
Mean	0.000106	0.000186
Median	0.000437	0.000402
Std. Deviation	0.004333	0.005839
Kurtosis	1.505243	10.864320
Skewness	-0.293364	-0.118480
Minimum	-0.019914	-0.045970
Maximum	0.016224	0.055931
Jarque-Bera	54.0421 (0.0000)	7271.1026 (0.0000)
Observations	503	2819

Table {7.18}: *Summary Statistics for returns of the E-mini NASDAQ-100 Index*
NOTE: *Probability value in parentheses (rejecting the null hypothesis of normality/Jarque-Bera Test)*

The results for the FTSE-100 Index, FTSE-100 Index Future, NASDAQ-100 Index and E-Mini NASDAQ-100 Index Future over the two sub-periods are presented in Tables {7.19}-{7.26}, respectively.
For FTSE-100 index, the higher returns occur in October and March and lower in November and May and the hypothesis of January effect is rejected over the sub-period of pre-2008.

	Dependent variable: R_t (Return)			
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000110	0.000638	0.172760	0.8629
February	0.000003	0.000662	0.005004	0.9960
March	0.000495	0.000624	0.793610	0.4278
April	0.000374	0.000688	0.544070	0.5866
May	-0.000255	0.000646	-0.394003	0.6937
June	0.000171	0.000638	0.267644	0.7891
July	-0.000223	0.000638	-0.349278	0.7270
August	-0.000126	0.000631	-0.198969	0.8424
September	0.000369	0.000654	0.564088	0.5729
October	0.000642	0.000624	1.028298	0.3043
November	-0.000564	0.000631	-0.893907	0.3718
December	0.000364	0.000679	0.535540	0.5925

Table {7.19}: *FTSE-100 Index over pre-2008 period (regression equation (5.12), method: least squares).*

For FTSE-100 index, the higher returns occur in April and July and lower in June and January and the hypothesis of January effect is rejected for the sub-period of 2008-2019.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	-0.000260	0.000326	-0.798495	0.4246
February	0.000167	0.000333	0.500800	0.6165
March	-0.000043	0.000336	-0.129360	0.8971
April	0.000508	0.000351	1.446465	0.1481
May	-0.000043	0.000349	-0.124495	0.9009
June	-0.000480	0.000340	-1.413244	0.1577
July	0.000431	0.000333	1.296069	0.1951
August	-0.000145	0.000341	-0.424481	0.6712
September	-0.000206	0.000338	-0.609418	0.5423
October	0.000046	0.000333	0.139359	0.8892
November	-0.000121	0.000339	-0.356614	0.7214
December	0.000379	0.000349	1.087059	0.2771

Table {7.20}: *FTSE-100 Index over post-2008 period (regression equation (5.12), method: least squares).*

For FTSE-100 index future, the higher returns occur in March and October and lower in November and May for the period 2006-2007. It is worth mentioning that returns for all months are not again statistically significant.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000058	0.000629	0.092154	0.9266
February	-0.000009	0.000652	-0.014559	0.9884
March	0.000598	0.000615	0.972302	0.3314
April	0.000365	0.000678	0.538800	0.5903
May	-0.000301	0.000636	-0.472657	0.6367
June	0.000217	0.000629	0.345553	0.7298
July	-0.000286	0.000629	-0.454472	0.6497
August	-0.000078	0.000615	-0.127361	0.8987
September	0.000485	0.000644	0.752359	0.4522
October	0.000578	0.000615	0.940551	0.3474
November	-0.000557	0.000622	-0.895478	0.3710
December	0.000276	0.000669	0.412812	0.6799

Table {7.21}: *FTSE-100 Index Future 2006-2007 (regression equation (5.13), method: least squares).*

For FTSE-100 index future over the sub-period of post-2008, the higher returns occur in April and July and lower in June and January and the hypothesis of January effect is rejected for the sub-period of 2008-2019.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	-0.000260	0.000326	-0.797450	0.4253
February	0.000250	0.000334	0.749520	0.4536
March	-0.000124	0.000336	-0.367621	0.7132
April	0.000554	0.000352	1.577431	0.1148
May	0.000012	0.000350	0.035758	0.9715
June	-0.000556	0.000340	-1.634577	0.1022
July	0.000443	0.000333	1.330549	0.1834
August	-0.000046	0.000342	-0.134004	0.8934
September	-0.000258	0.000339	-0.761490	0.4464
October	0.000045	0.000333	0.134992	0.8926
November	-0.000042	0.000339	-0.124218	0.9011
December	0.000205	0.000349	0.587840	0.5567

Table {7.22}: *FTSE-100 Index Future 2008-2019 (regression equation (5.13), method: least squares).*

Tables {7.23} and {7.24} detail the result of the ordinary least squares model for the two sub-periods in US cash market (NASDAQ-100 index). For NASDAQ-100, the results show higher returns in October, September and August and lower in February and July for the sub-period 2006-2007. However, all the p-value of T-tests is statistically insignificant and the hypothesis of January effect is rejected. From Table {7.24}, it is obvious that July has the highest mean return, while June has the lowest mean return for the sub-period 2008-2019. July is also found to have significantly average returns, since t-statistic values is higher than 1.96.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000414	0.000747	0.553802	0.5800
February	-0.000469	0.000767	-0.611227	0.5413
March	0.000248	0.000705	0.351696	0.7252
April	0.000564	0.000757	0.745841	0.4561
May	-0.000415	0.000713	-0.582362	0.5606
June	0.000003	0.000721	0.004241	0.9966
July	-0.000463	0.000738	-0.627472	0.5306
August	0.000703	0.000697	1.008412	0.3138
September	0.001071	0.000757	1.415776	0.1575
October	0.001106	0.000705	1.570314	0.1170
November	-0.000372	0.000729	-0.509893	0.6104
December	-0.000232	0.000747	-0.310349	0.7564

Table {7.23}: *NASDAQ-100 Index 2006-2007 (regression equation (5.12), method: least squares).*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000049	0.000383	0.128648	0.8976
February	0.000339	0.000393	0.863704	0.3878
March	0.000469	0.000385	1.218089	0.2233
April	0.000507	0.000395	1.284671	0.1990
May	0.000276	0.000392	0.704486	0.4812
June	-0.000328	0.000389	-0.844683	0.3984
July	0.000809	0.000391	2.067132*	0.0388
August	0.000041	0.000383	0.106936	0.9148
September	0.000026	0.000398	0.065576	0.9477
October	0.000026	0.000384	0.068151	0.9457
November	0.000030	0.000399	0.076334	0.9392
December	0.000034	0.000392	0.086303	0.9312

Table {7.24}: *NASDAQ-100 Index 2008-2019 (regression equation (5.12), method: least squares).*
Note: ** significant at the 5 per cent level*

For E-Mini-NASDAQ-100 index future, the results show higher returns in October, September and August and lower in July and February for the sub-period 2006-2007. In fact, all the p-values of t-tests are insignificant indicating that there is no significant month of monthly effect during 2006-2007 and the hypothesis of January effect is rejected. From Table {7.26}, it is obvious that July has the highest mean return, while June has the lowest mean return for the sub-period 2008-2019. Again, July is also found to have significantly average returns, since t-statistic values is higher than 1.96.

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
January	0.000302	0.000678	0.445016	0.6565
February	-0.000497	0.000705	-0.704774	0.4813
March	0.000166	0.000648	0.256486	0.7977
April	0.000448	0.000687	0.651878	0.5148
May	-0.000434	0.000655	-0.663233	0.5075
June	-0.000060	0.000662	-0.090224	0.9281
July	-0.000506	0.000678	-0.745919	0.4561
August	0.000584	0.000640	0.912236	0.3621
September	0.000946	0.000696	1.359835	0.1745
October	0.000977	0.000648	1.508590	0.1320
November	-0.000455	0.000670	-0.679348	0.4972
December	-0.000293	0.000687	-0.426295	0.6701

Table {7.25}: *E-Mini-NASDAQ-100 Index Future 2006-2007 (regression equation (5.13), method: least squares).*

Variable	*Coefficient*	*SE*	*t-statistic*	*Probability*
	Dependent variable: R_t (Return)			
January	0.000028	0.000375	0.074864	0.9403
February	0.000357	0.000384	0.929256	0.3528
March	0.000465	0.000376	1.236007	0.2166
April	0.000489	0.000384	1.274359	0.2026
May	0.000292	0.000384	0.760458	0.4470
June	-0.000335	0.000380	-0.879677	0.3791
July	0.000787	0.000381	2.065873*	0.0389
August	0.000054	0.000375	0.144928	0.8848
September	0.000022	0.000390	0.057452	0.9542
October	0.000010	0.000374	0.025638	0.9795
November	0.000049	0.000390	0.126513	0.8993
December	0.000003	0.000382	0.007075	0.9944

Table {7.26}: *E-Mini-NASDAQ-100 Index Future 2008-2019 (regression equation (5.13), method: least squares).*
Note: ** significant at the 5 per cent level*

Hence, it is noticeable that there is no January effect in US over the two sub-periods examined.
Furthermore, the January effect can be examined by a simply test for significance of the estimated coefficient α_1 in regression (1).
The above regression should show significant positive slope coefficient to indicate a January effect. Tables {7.23}-{7.30} present results for US and UK spot and futures indices, respectively. The dummy variable of January (α_1 of D_1) is not significant for all indices, and therefore the hypothesis of unusual large stock and futures returns is rejected. These findings confirm previous results obtained from the other regression equation.

Variable	*Coefficient*	*SE*	*t-statistic*	*Probability*
	Dependent variable: R_t (Return)			
Method: least squares				
a_0	0.000110	0.000193	0.568420	0.5700
a_1	0.000001	0.000663	0.000461	0.9996
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.23}: *FTSE-100 Index over pre-2008 period.*

Variable	*Coefficient*	*SE*	*t-statistic*	*Probability*
	Dependent variable: R_t (Return)			
Method: least squares				
a_0	0.000043	0.000102	0.415663	0.6777
a_1	-0.000303	0.000342	-0.886702	0.3753
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.24}: *FTSE-100 Index over post-2008 period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000114	0.000190	0.598874	0.5495
a_1	-0.000056	0.000653	-0.085888	0.9316
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.25}: *FTSE-100 Index Future over pre-2008 period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000042	0.000103	0.412222	0.6802
a_1	-0.000303	0.000342	-0.884598	0.3764
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.26}: *FTSE-100 Index Future over post-2008 period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000167	0.000219	0.762635	0.4460
a_1	0.000247	0.000777	0.317578	0.7509
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.27}: *NASDAQ-100 Index over pre-2008 period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000202	0.000118	1.716964	0.0861
a_1	-0.000153	0.000401	-0.381777	0.7027
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.28}: *NASDAQ-100 Index over post-2008 period.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000098	0.000202	0.484187	0.6285
a_1	0.000204	0.000706	0.289343	0.7772
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.29}: *E-Mini-NASDAQ-100 Index Future 2006-2007.*

Dependent variable: R_t (Return)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000199	0.000115	1.734204	0.0830
a_1	-0.000171	0.000392	-0.437464	0.6618
Note: $R_t = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.30}: *E-Mini-NASDAQ-100 Index Future 2008-2019.*

7.3 Monthly Effect-Volatility

7.3.1 Entire Period

The impact of January effect in volatility of spot and futures indices is tested by a simply test of significance of the estimated coefficient α_1 in a second regression as follows:

$$V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t \qquad (2)$$

Where $V_{RS,t}$ is the Rogers and Satchell volatility measure; D_1 takes the value 1 since the daily volatility at day t belongs to January, α_1 is the mean daily volatility of (spot or futures) index in January, and ε_t is an error term assumed to be independent and identically distributed.

The above regression should show significant positive slope coefficient to indicate an important impact of January effect on volatility. Tables {7.30}-{7.33} present results for US and UK spot and futures indices, respectively. However, the dummy variable of January (α_1 of D_1) is not significant for all indices rejecting the seasonality in volatility.

Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000089	0.000004	22.207354*	0.0000
a_1	0.000019	0.000013	1.398842	0.1620
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.30}: *FTSE-100 Index (entire period).*
Note: ** significant at the 5 per cent level*

Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000151	0.000008	19.22838*	0.0000
a_1	-0.000016	0.000026	-0.593191	0.5531
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.31}: *FTSE-100 Index Future (entire period).*
Note: ** significant at the 5 per cent level*

Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000109	0.000005	19.77028*	0.0000
a_1	-0.000003	0.000019	-0.145749	0.8843
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.32}: *NASDAQ-100 Index (entire period).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
	Dependent variable: $V_{RS,t}$ (Volatility estimator)			
Method: least squares				
a_0	0.000167	0.000007	23.200118*	0.0000
a_1	0.000019	0.000025	0.756585	0.4493
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.33}: *E-Mini-NASDAQ-100 Index Future (entire period).*
Note: ** significant at the 5 per cent level*

7.3.2 Two Sub-periods

Tables {7.34}-{7.41} present results for US and UK spot and futures indices for the two sub-periods, respectively. However, the dummy variable of January (α_1 of D_1) is not significant for US spot and futures indices rejecting the seasonality in volatility. In the case of the January effect in volatility for UK spot and futures indices over the sub-period 2006-2007 dummy variables of January are significant, and therefore, the hypothesis of January effect in volatility is accepted, while during the sub-period 2008-2019 both slope coefficients are not significant indicating a non-existence of January effect.

Variable	Coefficient	SE	t-statistic	Probability
	Dependent variable: $V_{RS,t}$ (Volatility estimator)			
Method: least squares				
a_0	0.000055	0.000003	16.890785*	0.0000
a_1	-0.000031	0.000011	-2.758670*	0.0060
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.34}: *FTSE-100 Index (2006-2007).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
	Dependent variable: $V_{RS,t}$ (Volatility estimator)			
Method: least squares				
a_0	0.000095	0.000005	20.216859*	0.0000
a_1	0.000027	0.000016	1.716619	0.0862
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.35}: *FTSE-100 Index (2008-2019).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Method: least squares				
a_0	0.000064	0.000003	19.22838*	0.0000
a_1	-0.000031	0.000012	-2.683788*	0.0075
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.36}: *FTSE-100 Index Future (2006-2007).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Method: least squares				
a_0	0.000167	0.000009	18.102257*	0.0000
a_1	-0.000014	0.000031	- 0.454529	0.6495
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.37}: *FTSE-100 Index Future (2008-2019).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Method: least squares				
a_0	0.000079	0.000004	18.432309*	0.0000
a_1	-0.000002	0.000015	-0.155539	0.8765
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.38}: *NASDAQ-100 Index (2006-2007).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Method: least squares				
a_0	0.000114	0.000006	17.726517*	0.0000
a_1	-0.000003	0.000022	-0.148400	0.8820
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.39}: *NASDAQ-100 Index (2008-2019).*
Note: ** significant at the 5 per cent level*

Variable	Coefficient	SE	t-statistic	Probability
Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Method: least squares				
a_0	0.000098	0.000005	19.857278*	0.0000
a_1	-0.000013	0.000017	-0.744099	0.4572
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.40}: *E-Mini-NASDAQ-100 Index Future (2006-2007)*
Note: ** significant at the 5 per cent level*

Dependent variable: $V_{RS,t}$ (Volatility estimator)				
Variable	***Coefficient***	***SE***	***t-statistic***	***Probability***
Method: least squares				
a_0	0.000179	0.000008	21.310400*	0.0000
a_1	0.000023	0.000029	0.808757	0.4187
Note: $V_{RS,t} = a_0 + a_1 D_1 + \varepsilon_t$				

Table {7.41}: E-Mini-NASDAQ-100 Index Future (2008-2019)
Note: ** significant at the 5 per cent level*

CHAPTER 8
Conclusions

The goal of this dissertation is to explicitly examine the volatility before and after the financial crisis of 2008 and to analyze the monthly effect on daily returns and in volatility in the UK and the US futures and spot markets. In this study, the Floros (2009) models are used to model volatility adopting four models based on open, closing, high and low daily prices during the entire period 2006-2019 and during the two sub-periods pre-2008 (2006-2007) and post-2008 (2008-2019). In particular, by means of this methodology, the daily prices can be characterized by volatility models. The empirical analysis was applied on the total of 13299 daily observations for FTSE-100 stock index, FTSE-100 Index Future, NASDAQ-100 spot index and E-mini NASDAQ-100 Index Future, arising from 3330, 3333, 3313 and 3323, respectively, trading days for each index. Additionally, the other objective of this dissertation to examine the seasonal effects on daily returns and in volatility, in the US and UK markets, was implemented by using an OLS model from data comprised of daily closing prices of the US and the UK cash and futures indices before and after financial crisis of 2008 (entire period and two sub-periods).

The empirical findings are summarized as follows. First, in the entire period of study (2006-2019), the results show that V_s, a simple measure of volatility defined as the logarithmic difference between the high and low prices, overestimates V_{gk}, V_p and V_{rs}. In the two sub-periods of 2006-2007 and 2008-2019, the results are exactly consistent with aforementioned overestimation. It has to be pointed out that these findings are in line with Floros (2009). In addition, the means of the simple, Parkinson, Garman-Klass and Rogers-Satchell volatility estimates are higher in futures markets (UK &US) in comparison with cash markets during the entire period and the two sub-periods. Another major outcome of the present study is that daily volatilities for both the NASDAQ-100 and FTSE-100 spot and futures indices are informative about the variability in the cash and futures markets. Second, the means of volatility estimators seem to have higher values during post-2008 period compared to pre-2008 period. Third, the results from an OLS model show that there is no January effect in the UK and the US during the entire period and the two sub-periods. For FTSE-100 spot and futures indices, the higher returns occur in April, and lower in June during the entire period 2006-2019. On the contrary, for NASDAQ-100 index and E-mini-NASDAQ-100 index future, the results show higher returns in July and lower in June during 2006 to 2019. For FTSE-100 index, the higher returns occur in October and lower in November over the sub-period of pre-2008, while the results show higher returns in April and lower in June for the sub-period of 2008-2019. For FTSE-100 index future, the higher returns occur in March and lower in November over the sub-period of pre-2008, while the results show higher returns in April and lower in June for the sub-period of 2008-2019. Additionally, for NASDAQ-100, the results show higher returns in October and lower in February for the sub-period 2006-2007, whereas the higher returns occur in July and lower in June during the sub-period 2008-2019. For E-Mini-NASDAQ-100 index future, the results show higher returns in October and lower in July over the sub-period of 2006-2007, while higher returns occur in July and lower in June for the sub-period 2008-2019. These findings confirm results obtained from the test for significance of the coefficient a_1 in regression equation (1) rejecting the hypothesis of unusual large stock and futures returns in January. In accordance with previous studies (Mehdian and Perry (2002); Patel (2016)) substantial evidence of non-existence of the

January effect is reported. Finally, the findings of this dissertation are in contrast with Rendon and Ziemba (2007).

Regarding the impact of January effect in volatility of spot and futures indices, the hypothesis of January effect in volatility is accepted for FTSE-100 cash and stock index futures markets over the sub-period 2006-2007, since dummy variables of January from equation (2) are significant. So, a significant negative January effect is found for the sub-period 2006-2007 that seems to produce a negative pressure on volatility in January for the UK market. However, in all other cases, the seasonality in volatility is rejected.

The above empirical findings are strongly recommended to risk managers dealing with the US and UK spot and futures indices. Investors should notice that January has not abnormal returns, not standing for a good time to invest in market, and they should consider adjusting their hedging strategies so as to minimize risk associated with spot and futures trading. Further research may (i) study the volatility asymmetries in the US and the UK cash and stock index futures markets using VAR models, (ii) and investigate further the causal relationship between futures volatility and trading volume that can leads to the improvement of ability to forecast futures prices.

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Appendix

FTSE-100 Index Futures Contract Specifications

Underlying Asset: FTSE-100 (a market-capitalization weighted index of UK listed blue chip companies

Commodity Code: Z

Unit of Trading: Contract Valued at £10 per index point (e.g. value £65,000 at 6,500.0)

Delivery Months: 4 quarterly months from in the March, June, September, December quarterly cycle

Quotation: Index points (e.g. 6500.0)

Minimum price fluctuation (Tick): 0.5 (£5.00)

Settlement Date: First business day after the Last Trading Day

Last Trading Day: Third Friday in delivery month, Trading shall cease as soon as reasonably practicable after 10:15 (London time) once the Expiry Value of the Index has been determined.

Exchange Delivery Settlement Price: The value of the FTSE-100 Index is calculated by FTSE International with reference to the outcome of the EDSP intra-day auction at the London Stock Exchange carried out on the Last Trading Day.

Final Settlement: Cash settlement based on the Exchange Delivery Settlement Price

Block Trade Minimum: 500

E-mini-NASDAQ-100 Index Futures Contract Specifications

Underlying Asset: NASDAQ-100

Commodity Code: NQ

Unit of Trading: Contract Valued at $20 per index point

Delivery Months: 4 quarterly months from in the March, June, September, December quarterly cycle

Quotation: Index points

Minimum price fluctuation (Tick): 0.25 ($5.00)

Settlement Date: First business day after the Last Trading Day

Last Trading Day: Third Friday in delivery month, Trading shall cease at 09:30 once the Expiry Value of the Index has been determined.

Final Settlement: Special Opening Quotation of the Nasdaq-100 Index to be determined by the Nasdaq Stock Market Inc..