NUI MAYNOOTH

Ollscoil na hÉireann Má Nuad

QUANTIFYING THE EFFECTS OF NEW DERIVATIVE INTRODUCTION ON EXCHANGE VOLATILITY, EFFICIENCY AND LIQUIDITY

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Summary

This thesis investigates the effects of the introduction of new financial derivative products on exchange volatility, efficiency and liquidity. The derivatives under primary investigation are Exchange Traded Funds (ETFs) and Contracts for Difference (CFDs). These products offer a cheap, tax-efficient and speedy method for increasing or decreasing market exposure to price changes in the related primary asset. By facilitating faster and shorter-term trading, these products may increase market liquidity and/or increase market volatility for the related primary asset. The thesis builds a cross-country database of new-derivative-markets opening dates, and investigates the key features of prices and returns for related primary assets before and after the opening of these derivative markets. The database covers 16 countries in the CFD investigation, 21 commodity markets in the ETF investigation, and related data as available (daily closing prices, trading volumes, bid-ask quotes) in each of them. The key price and return features investigated include bid-ask spreads, trading volumes (both of derivatives and related primary assets), and daily return autocorrelation, variance, skewness and kurtosis.

This thesis also considers a separate, but related, research problem. It extends and empirically applies a liquidity-indicator model for the Eurozone created by the Bank of England (BOE) and developed further by the European Central Bank (ECB) by including commodity liquidity, and uses this extended model to investigate shifting investor behaviour based on changing market dynamics. Similar to the investigation of the CDF and EFT markets, this investigation is concerned with market stability and liquidity in a changed environment (in this case, the key change is the introduction of the euro currency).

Chapter one contains an introduction to the main hypotheses regarding the effects of the introduction of new derivatives on securities markets, and the empirical methods used to test these hypotheses. This chapter also describes the two investment products which are the main focus, CFDs and ETFs, and their particular potential impacts on market-specific characteristics such as volatility, efficiency and liquidity.

Chapter two empirically investigates the impact of CFDs on market liquidity and volatility. CFDs have existed for less than twenty years and the CFD market grew rapidly prior to the recent international financial crisis. This chapter empirically examines the roles that CFDs have played, either as an accelerant for mispricing in international equity markets away from fundamental values, or as a source of increased market efficiency through the addition of new liquidity. This chapter uses GARCH and EGARCH models to test for the impact of CFDs on the return volatility and autocorrelation of the underlying security. In the case of Australia, the analysis is applied to individual securities. In the other 15 countries investigated in this chapter, the analysis is applied at the level of the market index. The chapter also investigates whether the stylised characteristics of CFDs are more or less pronounced in low liquidity exchanges. This chapter finds that CFDs appear to have influenced asset-specific variance

and return autocorrelation. Some tentative explanations for these findings are offered. The presence of bid and ask-price ‘overhangs’ associated with CFD trading cannot be rejected and may be associated with observed volatility reductions in some jurisdictions.

Following the analysis based on CFDs in chapter two, ETFs are the primary focus of chapter three. ETFs have existed since the late 1980s, but were first traded on commodity markets in the early 2000s. Their inception has been linked by some market analysts with the large growth in commodity market volatility seen in recent years. This chapter directly tests this link. The chapter also investigates whether the stylised characteristics of ETFs are more or less pronounced in larger commodity markets than in smaller markets. The results indicate that larger ETFs in terms of their assets under management at their dates of inception, are associated with higher volatility. Smaller commodity markets are found to have increased efficiency after the introduction of ETFs, indicating that there are some benefits from new ETF investment in markets below $4 to $5 billion in size, but the associated caveat is that of increased volatility, indicative of potential pitfalls in the ETF portfolio rebalancing process. It appears that ETFs have made commodity markets more efficient through a new influx of trading counterparties, but they appear to be associated with a cost. The need for regulation of investment size and market ownership limits therefore cannot be rejected.

Chapters two and three look at two particular new instruments and their effects on liquidity and volatility. Another major innovation in market structure was the advent of the euro currency in January 1999. The power and presence of a financially-combined Europe attracted new international investment, therefore influencing liquidity. The combination of this influx of investors and new products (including CFDs and ETFs) can potentially have wide market impacts. Understanding the structural changes of liquidity in Europe in recent years is important for macroprudential risk assessment, as sudden changes in conditions may be indicative of current stress and a signal of future stress. Chapter four presents a European-specific liquidity measure used by several central banks, and provides some new modifications to this measure. The measure is constructed by combining several facets of liquidity and depth measurement across several asset markets. It attempts to incorporate aspects such as market tightness, depth and resiliency. The flows and the direction of causality can also be inferred using vector autoregression, Granger causality techniques and impulse response functions. The measure uses a combination of liquidity determinants including the bid-ask spread, the return to volume ratio and numerous measures of liquidity premia. In the chapter, the modified liquidity measure is applied empirically to European-area data.

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To my father John, I owe you everything.

Conferences and Publications

I have presented Chapter 2 titled '*Contracts for Difference: Added liquidity or excess volatility?*' at the National University of Ireland Maynooth Ph.D Internal Seminars (May 2010) and at the Central Bank of Ireland Internal Seminars (April 2011). This paper was also accepted for presentation at the Irish Economics Association at the 25th annual conference in Limerick (April 2011). Shortened versions of Chapter 2 titled 'How have CFDs affected equity market volatility?' have been submitted to the Central Bank of Ireland for submission as both part of the Economic Letter Series (December 2011) and Research Technical Paper Series (February 2012)

I have presented Chapter 3 titled '*Have Exchange Traded funds influenced commodity volatility?*' at the Central Bank of Ireland Internal Seminars (November 2010). Shortened versions of chapter 3 using the same title, have been submitted to the Central Bank of Ireland for submission as both part of the Economic Letter Series (August 2011) and Research Technical Paper Series (August 2011).

I have presented Chapter 4 titled '*European financial market liquidity?*' at the National University of Ireland Maynooth Ph.D Internal Seminars (June 2011) and at the Central Bank of Ireland Internal Seminars (June 2011). A shortened version of Chapter 4 was submitted for publication in the Central Bank of Ireland's Macroprudential Risk Assessment (*forthcoming* Q2 2012).

To my father

Chapter 1: The effects of new derivatives on market dynamics

Abstract: *This thesis investigates the effects of the introduction of new financial derivative products on exchange volatility, efficiency and liquidity. The derivatives under primary investigation are Exchange Traded Funds (ETFs) and Contracts for Difference (CFDs). ETFs have existed since the late 1980s, but have only been traded on commodity markets since the early 2000s. CFDs made their first appearance in equity markets in the late 1990s and have since grown significantly to become one of the most frequently traded products across numerous financial markets. This chapter introduces and explains the dynamics and characteristics of these new investment products and their relationship with market-specific characteristics such as volatility, efficiency and liquidity.*

1.1. Introduction

New investment products, such as CFDs and ETFs, are created to enable investors to take advantage of new investment approaches and strategies or to avoid costly regulations. These products create new leveraged strategies for the investors who use them and have been linked to increased market efficiency through the quicker and more effective transfer of information across financial markets (Gastineau, 2010, Kosev and Williams, 2011). In recent decades we have witnessed a comprehensive growth in the use of leveraged[1] products designed to enable trading strategies exploiting the spread between investment products. This has potential benefits, such as diversification in the form of that discussed by French and Poterba (1991) and Goetzmann and Kumar (2008), through the use of ETFs and leveraged spread-betting[2] through CFDs. Investing in international ETFs helps to reduce home bias (excessive investment in the investor's home territory) thereby providing more substantial diversification. CFDs have also increased the availability of foreign investment opportunities for domestic investors. This thesis attempts to investigate the effects that tradable products such as CFDs and ETFs have had on volatility and liquidity.

This thesis focuses specifically on the role that these products have had in influencing volatility in the cash and futures markets for equities and commodities. Derivatives such as CFDs and ETFs are developed by a primary broker or sponsor and are then offered to investors who seek additional risk in their portfolios through leverage, to which they gain

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[1] Leverage is the term to describe any technique used to increase the potential return of an investment using borrowed margin. Common methods of obtaining leverage include borrowing money, buying fixed assets and using derivatives.
[2] Spread betting is based on wagering on the outcome of an event, where the pay-off is based on the accuracy of the wager, rather than a simple 'win or lose' outcome such as those offered when betting. A spread is a range of potential outcomes and the bet is based on whether the outcome will be above or below the spread.

access to when the broker provides margin[3]. CFDs offer cheap access to investment credit. When an investor selects CFDs as their method of investment, they are partaking in a contract where they are borrowing funds from the CFD provider on which overnight interest is charged. This interest cost is potentially cheap for short-term investment, but may be expensive for investors with longer-term investment horizons. The standard margin provision internationally for CFDs is 10%, with the remaining 90% of the investment borrowed by the investor from their broker. CFDs are investigated in detail in section 1.2.

ETFs are structured differently. The ETF sponsor purchases large amounts of the asset on which the fund is based and then sub-divides and re-allocates elements of the same pooled funds to investors seeking to invest. This provides the investor with easy access to markets which they may have being unable to access otherwise due to, for example, trading restrictions such as large entrance-capital requirements and trading commissions (Blitz et al., 2010). ETFs have raised significant issues in some markets since the size of the fund has in some cases exceeded 40-50% of the total market. This dominant position could hinder the dynamics of the market. ETFs have also been viewed as a source of ignition and potential accelerant of commodity price increases and volatility (Cheng and Madhavan, 2009). Also, the ease of access and reduced trading commissions have created a product that has been found to appeal directly to 'noise traders' (Cherry, 2004, Ackert and Tian, 2008), thus appealing to a group of investors that have been found to increase volatility in exchanges that they enter (Mendel and Shleifer, 2011). ETFs are discussed in detail in section 1.3 while the nature of the effects of both CFDs and ETFs on international market liquidity is investigated in section 1.4.

1.2. Contracts for Difference (CFDs)

The characteristics of CFDs are structured towards those investors seeking additional levels of risk in their portfolios. CFDs are usually structured to allow an investor to invest at a standard rate (based on jurisdictional regulatory differences) of 10%. This CFD borrowing mechanism is effectively an alternative method of gaining access to investable funds and is available to all investors contingent on the margin that they initially provide. This same margin provision grants the investor an opportunity to leverage themselves tenfold, since this investment offers the capability of purchasing ten times the amount of equity than they could previously afford (assuming the standard rate of 10% margin is used). If the investor has purchased the equity and if the price increased 10%, the investor has made 100% returns. But if the share price falls 10%, the investor has now lost his/her entire position and must meet margin calls[4] to maintain the position's active status.

[3] Margin buying is buying securities with cash borrowed from a broker, using other securities as collateral. This has the effect of magnifying any profit or loss made on the securities. The securities themselves serve as collateral for the loan. The net value is initially equal to the amount of one's available capital and this must stay above a minimum margin requirement which is present to protect the broker against a fall in the value of the securities to the point where the investor can no longer cover the loan.

[4] A margin call is a broker's demand on an investor using margin to deposit additional money or securities so that the margin account is brought up by the minimum maintenance margin.

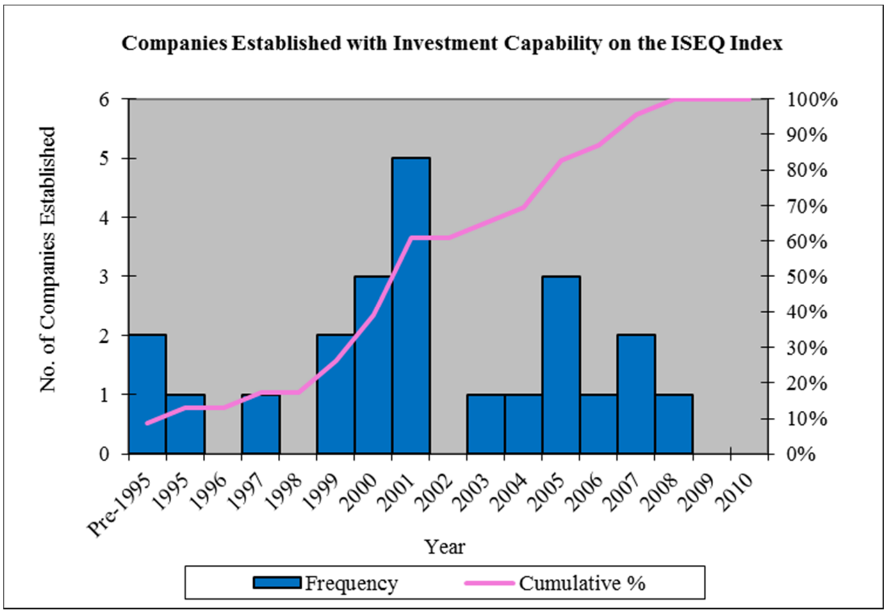
To investigate the profits CFDs can generate, we can use a hypothetical example of the company ABC plc. An investor uses CFDs to invest €10,000 at a price of €1.20 per share. If the investor had bought the shares through traditional stockbroker channels at 100% margin, he would receive 8,333 shares. Using CFDs at a standard 10% margin he can now afford 83,333 shares, though he would hold none of the voting rights on the shares. In industry terminology, the investor is now 'long €833.33 per point' indicating a gain or loss of €833.33 for every cent move above or below €1.20. To open the same position using a stockbroker, the investor would require €100,000 in initial capital. The speculative nature of the position is evident if the investor does not have the €100,000 necessary to fully protect their portfolio should the price of ABC plc. equity fall to €0.00. The investor in fact would lose all initial capital should the share price fall to €1.08 and would gain €10,000 if the share price increases to €1.32. If for example, the share price increased to €2.40 and if the investor had invested with a stockbroker, he/she would now possess €20,000. Using CFDs, he/she would receive €110,000.

From the example above, it is clear that CFD can increase both trading volumes and market volatility as traders enter and exit their leveraged positions. Brunnermeier, (2008) finds that trading of volumes of leveraged financial instruments thrives in periods of short-term extreme volatility, such as that seen in the 2007 to 2011 financial crises, as investors maximise the amount of a particular equity that they can afford. Evidence of this phenomenon was also uncovered in the build-up to the subprime crisis (Smith and Pulliam, 2007). Due to overnight interest charges and trading commissions, long-term investors would shy away from using CFD. Specifically, more high-frequency, speculative traders would find CFDs more attractive as an investment product. This group have been associated with increased market volatility (Avramov, Chordia and Goyal, 2006).

Along with large CFD trading volumes, there have been instances of trading irregularities associated with CFD investment. The report of the Irish Banking Commission which investigated the systemic banking crisis in Ireland found that an 'overhang' existed from large CFD trades that was capable of leading to confusion and differing interpretations of what was driving the share price collapse of Anglo Irish Bank (Report of the Commission of Investigation into the banking sector in Ireland, 2011)). In Germany, a report by the ESME[5] in 2009 found that a large unwinding by Porsche of options relating to CFDs in Volkswagen (VW) combined with take-over rumours, had fuelled a 500% price increase in less than seven days in October 2008 (European Securities Market Expert Group, 2009).

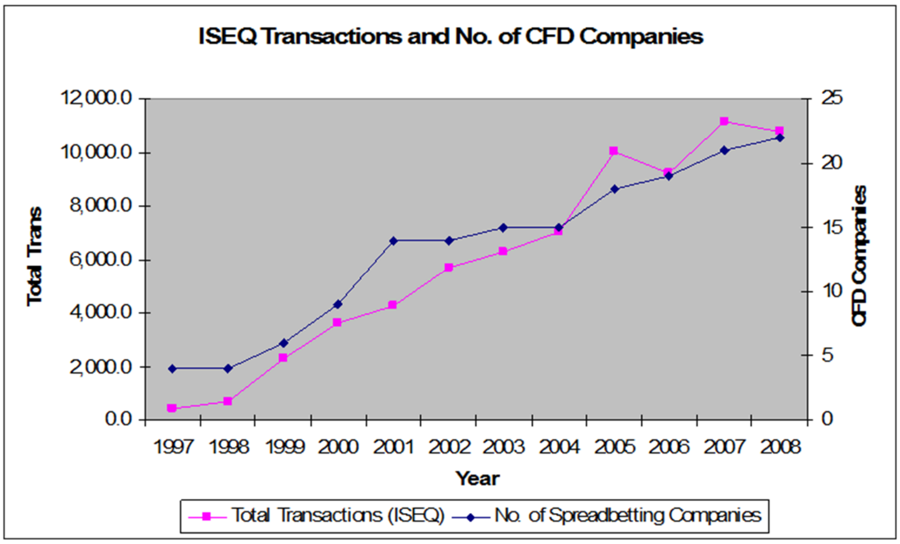
[5] The European Securities Market Expert Group (ESME) was established by the European Commission in March 2006 to provide legal and economic advice on the application of the EU Securities Directives. The ESME suspended its activities in December 2009.

Figure 1.1: *CFD investment capability in Ireland*



Note: Figure 1.1 shows the amount of CFD providers that offer shares on the ISEQ index as an investment product to their clients. A large proportion of the companies were established during the 'dot-com' era. Data is taken from a combination of the numerous company websites.

Figure 1.2: *ISEQ transactions and growth in CFD companies*



Note: The data on the number of total transactions is taken from the Irish Stock Exchange website (www.ise.ie). Figure 1.2 investigates the relationship between the number of transactions on the Irish Stock Exchange (ISEQ) and the number of CFD companies located in Ireland and the United Kingdom with investment capability on the ISEQ. We can see a clear positive correlation between the two variables.

CFD companies benefit significantly from the increased CFD volumes traded in periods of increased volatility. In figure 1.1, we can see the growth in CFD companies that offer equities on the ISEQ Index to their clients as a trading option. These companies advertise generally both as CFD and spread-betting companies. The major difference between the two is tax regulation. In some countries, such as Ireland and the United Kingdom, betting markets are free from all taxation. Alternatively, CFD investment may be subject to taxation on profits[6]. Apart from this CFDs and spread-betting are effectively the same.

Again, investigating the trend in the growth of CFD and spread-betting companies, evidence of their increasing importance can be measured in terms of the total growth in transactions. The ISEQ is a special case as there is no option or futures market available for leveraged trading. Growth in trading volumes on the ISEQ were the result of significant flows of funds coming from large investment firms (for example, hedge funds) and also from the growth of CFDs in Ireland and the United Kingdom. From figure 1.2, we can see the trends from 1997 until 2008 (due to data restrictions). We can clearly visualise the rapid growth in the number of spread-betting companies from 2000 onwards, whereas in 1997 there were only five established. The growth in the spread-betting and CFD industry is clearly in tandem with the growth in the level of total transactions on the ISEQ. Due to the leveraged nature of CFDs, the potential number of shares that could have been traded relative to fully margined investment is ten times greater. Also, as the Irish Stock Exchange (ISEQ) grew, more investors began to gain exposure to these new financial instruments, which may have led to an increase in the number of CFD companies. Dual causality, between transactions on the ISEQ and the growth of the CFD trading companies is the most likely explanation as the growth of the ISEQ would have increased awareness of CFDs as a trading mechanism and the growth of CFD companies may have increased the number of transactions through the provision of leverage. However, CFDs are not a common feature of all financial markets. Specifically, the United States has not allowed CFDs to be traded as a result of restrictions on over the counter[7] (OTC) financial instruments by the US Securities and Exchange Commission[8]. Thus CFDs on US equities are available to non-US residents only.

1.3. Exchange Traded Funds (ETFs)

Exchange-Traded Funds are typically registered investment funds that track an investment product or particular index. The components of these funds are traded in a similar manner to equities. For example, a financial ETF could potentially comprise a fund which has invested in the main financial elements of a particular exchange. The investment strategy of the ETF is decided by the provider and can be based, for example, on market capitalisation[9] or share price of the individual elements of the ETF. Investors can short[10] their chosen ETF and, in

[6] In Ireland, this is known as capital gains tax, charged on profits and has been around 20% in recent years.

[7] Over the counter (OTC) is to trade financial instruments directly between two parties, as opposed to exchange trading which occurs in exchanges such as cash, futures, options, etc.

[8] The US Securities and Exchange Commission (SEC) is an agency that has the primary role of enforcing the federal securities laws and regulating the securities industry (including stock, options, futures, etc.). The SEC was established by section 4 of the Securities Exchange Act (1934).

[9] Market capitalisation is a measure of size of a business enterprise equal to the share price times the number of shares outstanding (shares that have been authorized, issued, and purchased by investors) of a public company. As owning stock represents ownership of the company, including all its equity, capitalisation could represent the public opinion of a company's net worth and is a determining factor in stock valuation.

[10] Short selling is the practice of selling assets, usually securities that have been borrowed from a third party with the intention of buying identical assets back at a later date to return to the lender.

some cases, they can use leveraged products such as CFDs to increase their exposure. The price of the ETF varies based on supply and demand of investment and this price is visible throughout the trading day. ETFs attempt to replicate the return of an index, although it is not unusual to see significant differences in the returns of an index and the associated ETF (Svetina and Wahal, 2008, Agapova, 2010, Charupath and Miu, 2010).

The ETF creation process for funds domiciled in the United States begins when a prospective ETF manager (or 'sponsor') files a plan with the Securities Exchange Commission (SEC) to create an ETF. If the plan is approved, the sponsor forms an agreement with an 'authorised participant', usually a market maker, specialist or a large institutional investor, who is empowered to create or redeem ETF shares. In the case of equity ETFs, the creators often borrow equity from a pension fund or other large fund to form the creation unit. This can be the case for commodity ETFs, but given the large size of the positions being opened and the use of commodity futures markets, the positions are mostly built from direct purchases of the asset, rather than borrowing from a third party. Other international ETFs are formed in a similar manner, but they must satisfy the regulations of the jurisdiction in which they are domiciled.

ETF investors receive additional investment benefits from tax-efficiency in comparison with mutual funds[11] and, as ETFs track many of the indexes that they are synchronised with, there is a reduction in operating and transaction costs due to the passively-managed styles[12] of most ETFs (Anderson et al. 2010). The variety of ETFs available to investors cover nearly all sectors of international financial markets. Alternatively, ETF investors do have to pay commissions to their brokers that vary depending on the liquidity of the market in which they are investing.

ETFs have evolved in recent years becoming more complex (Kosev and Williams, 2011). It is now possible to buy shares of an ETF investing in the underlying index using additional leverage. Some funds are established already shorting the market, thus buying into the ETF creates a short position for the investor. This style of ETF is also known as an 'inverse ETF' and the product has become popular in the recent financial crises as many investors attempt to profit from falling market prices. Some funds offer positions based on market spreads[13]. The most common funds are based on the difference between the current market price of a product and the associated futures price[14]. There are an incredibly large number of variations possible for ETF creation.

[11] A mutual fund is a professionally managed type of collective investment scheme that pools money from many investors and invests typically in investment securities (stocks, bonds, commodities etc.). The mutual fund will have a fund manager that trades (buys and sells) the fund's investments in accordance with the fund's investment objective.

[12] Passive investing is a financial strategy in which a fund manager makes as few portfolio decisions as possible, in order to minimize transaction costs

[13] The market spread for securities is the difference between the prices quoted for an immediate sale (ask) and an immediate purchase (bid). The size of the bid-offer spread in a security is one measure of the liquidity of the market and of the size of the transaction cost.

[14] A futures contract is a standardized contract between two parties to buy or sell a specified asset of standardized quantity and quality at a specified future date at a price agreed today (the futures price). The contracts are traded on a futures exchange. Futures contracts are not "direct" securities like stocks, bonds, rights or warrants. They are still securities, however, though they are a type of derivative contract.

Many market analysts view ETFs as a tool offering an opportunity for smaller investors to enter markets they otherwise could not (Wang et al. 2010, Roll et al. 2011). In some financial markets, the costs of entry are simply too high for the average investor. The creators of ETFs are able to pool the investment funds of numerous investors, thus allowing direct market entry. The ETF then divides the portfolio into shares and sells these in a secondary market. There are many issues associated with this style of investment that have created some cause for concern. One concern is the ease of access for some investors who would otherwise have been unable to enter the market who can now enter and exit the market, as frequently and easily as they desire (Gutierrez et al. 2009). These investors are found to contribute to a facet of investment known as ‘noise trading’. This same style of investment has the potential to increase the volatility of the exchanges in which an ETF is invested in (FSA, 2010). This effect can also be amplified through the use of leveraged ETFs.

ETFs based on leverage are generally beneficial to those investors wishing to maximize their purchasing capability with a minimal nominal investment. FINRA[15] in 2009 reminded brokers of their fiduciary responsibilities when providing ETFs that offer leverage. In an official statement on their website[16], they reminded brokers and advisors that these instruments are ‘complex’ and that they are ‘unsuitable for investors who plan to hold them for more than one trading session’ (US Securities and Exchange Commission, 2011).

Other significant problems with ETFs include investor trading habits. It has been found that ETF investor trading habits are associated with more frequent trading, which has been found to reduce overall market returns (Madhavan, 2009). John Bogle, the founder of the Vanguard Group[17], has also argued that ETFs are the source of short-term speculative trading strategies. Though offering the view that an ETF held for a prolonged period of time can be a good investment, the trading commissions significantly reduce the returns to the investor and that the investor may not receive the diversification initially offered by the ETF provider. Another problem cited by Bogle (2010) with ETFs is the significant lack of investor and market knowledge about the product.

It has also been argued that indices that are offered as an ETF may be misrepresented (Haskin et al. 2009). Though it may be based on a particular sector of the economy or market, it is at the discretion of the ETF creator which individual components are in the fund. Higher market volatility is also associated as a leading cause of tracking error[18] between the returns of the ETF and the returns of the market. In most cases, ETFs have a low tracking error. But in markets with low market liquidity, there are significant issues for traders attempting to immediately execute orders on behalf of clients or investment funds, thus they may have to pay more for this immediate order execution.

[15] Financial Industry Regulatory Authority (FINRA) is the largest independent regulator for all securities firms doing business in the United States. They oversee nearly 4,700 brokerage firms, 167,000 branch offices and 635,000 registered securities representatives.

[16] The FINRA website can be found at http://www.finra.org.

[17] The Vanguard Group is an American investment management company that manages approximately $1.4 trillion in assets, based in Malvern, Pennsylvania. It offers mutual funds and other financial products and services to individual and institutional investors in the United States and abroad.

[18] Tracking error is a measure of how closely a portfolio follows the index to which it is benchmarked.

The main benefits of ETF investment is the ease of diversification, low expense ratios and tax efficiency (Gastineau, 2010). This comes with all the standard structure of a normal equity with options[19], short selling, stop-losses[20] and limit orders[21] available. ETFs have lower operational costs as most are passively managed, thus ETF managers do not actively buy and sell the individual elements of the ETF, but rather hold the components for long term growth opportunities. ETFs can be bought and sold at any time during the trading day in comparison to mutual funds that can only be sold at the end of each trading day when their net asset value (NAV) is calculated. As an ETF investor, it is also possible to see the components of the ETF at regular intervals during the trading day, thus making ETFs more transparent than mutual funds. Other benefits include tax efficiency due to economies of scale and ease of exposure to markets that otherwise would not have been possible for the individual investor.

One of the major volatility linked issues associated with ETFs is the rebalancing trades that occur at the end of the trading day. For ETFs to meet their investment mandates, it is necessary for them to rebalance their portfolio as market movements require. Many analysts have thought for some time that it is this rebalancing process that is causing or even abetting excess volatility as seen in the work of Gardner and Welsh (2005), Rompotis (2008), Carver (2009) and Humphries (2010). Many market experts believe that ETF rebalancing due to the unwillingness and reticence to hold positions overnight is boosting late-day volume, with some estimates in the range of 20-30% of last hour trading being accredited to ETFs (Avellaneda and Zhang, 2009, Knain-Little, 2010). In 2010, a Morgan Stanley report estimated that ETFs accounted for about 30% of daily listed market volume, which is three times more than in 2005. The Investment Company Institute in 2010 believed that more than $780 billion is invested in ETFs (Milonas and Rompotis, 2006). Leveraged ETFs have drawn their own concerns due to the amplified volumes purchased and sold that are associated with fund rebalancing. If one was to investigate broad funds like index trackers, the rebalancing process of one large ETF investment could be as large as a buy or sell on every selected stock on the ETF index in question. Hundreds of billions of United States dollars of ETF funds capital is now invested in contracts that were once dominated by commodity producers and consumers who sought to hedge specifically against commodity-market volatility for day-to-day company risk reduction.

Another effect associated with increased ETF trading is a rise in market correlations (Roll, 2011). A 'herd effect'[22] has been seen by analysts as ETF trading mirrors falls in individual shares (Stoll and Whaley, 2010). This has been amplified by current global uncertainties, as investors are now less willing to hold overnight positions due to the increased risk of out-of-

[19] An option is a derivative financial instrument that establishes a contract between two parties concerning the buying or selling of an asset at a reference price during a specified time frame. The buyer of the option gains the right, but not the obligation, to engage in some specific transaction on the asset, while the seller incurs the obligation to fulfill the transaction if so requested by the buyer.

[20] A stop order (also stop loss order) is an order to buy (or sell) a security once the price of the security has climbed above (or dropped below) a specified stop price.

[21] A limit order is an order to buy a security at not more, or sell at not less, than a specific price.

[22] The 'herd effect' is defined as the widespread tendency to copy the actions of what a group or the crowd is completing or in other word to behave instinctively like most other people. In finance it is attached to the mentality of a large group of investors to follow a leader (i.e.: a large mutual fund or ETF) and invest when the price of a stock moves drastically in one direction.

market-hours price fluctuations. This phenomenon is clearly more pronounced since early 2008, signalling the change in risk preferences of investors as markets started to fall drastically. But to investigate this topic in depth, one would need to know the investment and rebalancing criteria of every fund in a particular sector. The best academics can do in this situation is work with total ETF volumes traded in equities and commodities as a proportion of total market volume and estimate rebalancing processes. Commodities may be slightly less complex as the investment pool is generally based solely on the main investment asset of the ETF.

ETFs are available on nearly every international financial exchange including commodity markets. Commodity prices such as those of oil and gold have reached unprecedented highs in recent years and questions have been asked as to the true source of this upward pressure. The same commodities are associated with a ‘flight to safety’ in volatile periods in equity markets. But ETFs now offer every investor an opportunity to gain from the rise in commodity prices associated with the same flight to safety. Some analysts believe that the amplified increase in the price of some commodities is directly-associated with the new-found mass investment from ETFs (Irwin and Sanders, 2009, Hailu and Weersink, 2010, Tilton et al. 2011). It was noted that even though some oil and gold ETFs invest in the futures markets of these same products, the funds possess the same market moving capability even though the futures price movements may be disassociated from the spot market price.

In July 2010, Bloomberg BusinessWeek introduced their magazine with the heading ‘Amber Waves of Pain, Do Not Buy Commodity ETFs!’ with commodity ETFs been brandished as ‘America’s worst investment’. Bloomberg stated before that many ETFs are ‘stuffed with exotic derivatives’ at risk of becoming ‘the next financial time-bomb’. This time-bomb is believed to have the capability of recreating the market panics of the early 2000’s and 2008 periods, simply due to the sheer scale of the investment involved. Much of the problem associated with commodity ETFs is the lack of understanding by investors as to the underlying mechanisms of how the funds work. One of the major issues as explained earlier was that of futures market ‘contango’ (Kosev and Williams, 2011). Instead of taking delivery on the futures contracts of the commodities ETF funds are primarily investing in, they sell the futures contracts prior to expiry and buy into more futures contracts with a long-term expiry. If for example, crude oil is currently $75, and the next month’s futures contract is $77 and the month after is $79, an ETF wishing to move from the near future contract to the next would take an immediate loss of $2 to replace the same asset. This represents an immediate loss to the investors in the ETF. Futures traders on the other side of the transaction are finding themselves profiting from far month contracts that are trading at enormous premiums to the front month due to the investment strategies of the ETF brokers. There in fact has been the recent creation of a sub industry of hedge funds to take advantage of this spread. Overall, commodity ETFs tend to own the nearest futures contract of the commodity they are investing in, while paying huge premiums leading to a large under-performance relative to the underlying investment product. Investors consider ETFs to be effective vehicles for gaining exposure to commodities in their portfolios.

Commodity ETFs have to buy more underlying commodity futures contracts in order to be able to issue additional shares—and there is growing concern at the Commodity Futures Trading Commission (CFTC) that the deluge of money pouring into these ETFs from retail investors may be distorting market prices. That is not the only difficulty faced by the asset class. On August 12th 2009, the United States Natural Gas Fund (UNG) was the first ETF to stop issuing new shares out of concern that it might already be exceeding strict position limits—the number of futures contracts it is allowed to hold—that the CFTC may impose in the near future. This move was echoed by ETF providers such as Deutsche Bank and Barclays Global Investors, who suspended further issuance of some of their shares without in depth explanation. It has been much anticipated that the funds also acted in anticipation of the CTFC ruling that would shut down very aggressive commodity products that were believed to be distorting market prices.

The Bank of England has also highlighted ETF market risks. They stated that the benefits of ETFs may be outweighed by “complexity, opacity and contingent risks” - and it is worried that the transparency of the risks arising from securities lending as many funds lend out the securities bought with retail investors’ money (Bank of England Financial Stability Report, June 2010). The Bank of England also believes that the auditing processes that should ensure the shares in ETFs are backed by an equivalent value of the underlying commodity or index may not be up to the task. The structure of the ETF market itself makes fraud easy. “Often, for tax and stamp duty reasons, as well as cost and finding the right legal framework, many ETFs are listed in one country, the management resides in a second, and the commodity or securities are held in a third,” Bedlam Asset Management warned in October last year (Hussain, 2010). It has unearthed ‘beverage’ ETFs where the manager, trustee, custodian and listing are in the Indian sub-continent, the Gulf, Africa and Europe which convinces them there are ETF frauds out there just waiting to be discovered as why would they not keep all elements of the ETF in a single jurisdiction if fraud were not allowed?

Whatever triggers a panic to exit the ETF market – fraud, the regulatory crack down, or simply general market panic – global equity prices are likely to be hit by a chain reaction. “Wall Street has created a dangerous new kind of global weapon of mass destruction – a bomb primed to detonate like the 2000 dot-coms, the 2008 sub-primes – and detonation is dead ahead,” Paul Farrell recently wrote in Dow Jones’ Market Watch (Farrell, 2010). If ETF funds become forced sellers to meet redemptions, it could create a downward spiral as a wave of physical gold and other commodities are sold into thin markets, in turn triggering falls in the share prices of companies that produce these commodities. As investors sell shares in the more concentrated ETFs, the very act of selling the underlying investments is likely to put pressure on commodity values, negatively effecting the ETF’s net asset value and precipitating additional sales.

CFTC Chairman Gary Gensler stated in an August 19th 2009 news release that "position limits should be consistently applied and vigorously enforced" and that "position limits promote market integrity by guarding against concentrated positions" (CFTC press release, August 19th 2009). This would have a negative impact on ETFs as investors would be less attracted if their positions were limited. ETF providers are of course opposed to any regulation limiting their products, but some markets that ETFs invest in are simply too small to efficiently absorb the large inflow of investors' funds. In a reversal of findings and decisions made in the United States by the Bush administration, the CFTC under the control of Gary Gensler concluded that speculators may have played a significant role in driving wild price swings in oil prices that caused oil to spike at $147 in mid-2008 (CFTC, 2008). Also, on May 6th 2010, the 'Flash Crash' of US equities saw more than 70% of the trades cancelled due to excessive declines involving ETFs, reinforcing the view on the impact of the massive influx of capital into commodities. The financial reform bill[23] that Barack Obama signed on the 21st of July 2010 included provisions that will allow for new rules to limit the amount of investments in commodities by big institutions betting on their direction purely for financial gain (or without any need for company specific hedging purposes) while it will impose regulatory caps on energy trading in the near future and limit the size of funds.

1.4. The impact of new investment tools such as CFDs and ETFs on market liquidity

Both ETFs and CFDs have the potential to increase market liquidity. CFDs, through the process of investor leverage based on the availability of trading margin, can increase liquidity in terms of trading volumes – directly as a result of the margin and hedging practices of CFD brokers. Whereas, investors who are fully margined can utilise x shares, CFD traders can potentially utilise $\frac{x}{\%\,margin}$ shares. Alternatively, when CFD brokers hedge the counterparty risk of their clients, they implement orders to buy and sell their holdings through limit orders and stop losses, the direction of which depends on whether it is a trade to buy or sell. Market depth[24], another significant barometer of liquidity, also increases based on the hedging actions of the broker. Both CFDs and ETFs, through their ease of use, margin capabilities, tax benefits and low trading commissions, both offer a useful platform for short-term day-traders[25] to enter the markets in which they choose to invest.

It is this same increase in trading frequency and volumes traded that have increased the liquidity and depth of some markets. In countries such as Ireland, there has been a correlated increase in liquidity of equity markets with that of the growth of the CFD industry. There have also been questions about the capability of smaller equity exchanges to absorb the volumes of margined trading products such as CFDs. ETFs alternatively are created baskets of numerous underlying assets. The major liquidity increasing effect is associated with the fact that small investors can rarely afford the significant charges, commissions and minimum purchasing values necessary to invest in commodity markets, yet ETFs offer an opportunity for all investors of all wealth categories to enter and exit their chosen markets with benefits such as added diversification from increased products in their portfolio (Booth and Fama, 1970). The significant growth of ETFs has been linked to the life-time high prices seen in oil

[23] Dodd-Frank Wall Street Reform and Consumer Protection Act, 111th Congress, 2009-2010

[24] Market depth refers to the size of an order needed to move the market a given amount. If the market is deep, a large order is needed to change the price. Market depth closely relates to the notion of liquidity, the ease to find a trading partner for a given order. A deep market is also known as a liquid market.

[25] Day trading refers to the practice of buying and selling financial instruments within the same trading day such that all positions are usually closed before the market closes for the trading day. Another name for this style is active trading.

and gold markets in recent years and in December 2010 it was reported that the Blackrock ETF market was worth over $1.48 trillion (Techchandani, 2011).

1.5. Conclusion

This chapter offers a concise overview of the investigated products and hypotheses contained in this thesis. This thesis investigates the effects of these relatively new investment products and their associated link with recent crises and market panics.

The market influence of new investment products such as CFDs and ETFs are the main focus of chapter 2 and chapter 3 respectively. These products have the power to add significant liquidity to numerous international exchanges and the effect of this must be investigated in terms of numerous market metrics of dynamics and efficiency. Chapter 4 develops an effective metric of European liquidity and its benefits towards macroprudential risk assessment. This chapter also contains analysis of the shifts in liquidity in the lead up to the international subprime crisis and European sovereign debt problems.

Chapter 2: Contracts for Difference: Added liquidity or excess volatility?

Abstract: *Contracts for Difference (CFDs) have existed for less than twenty years. Prior to the international crisis, the market grew rapidly. These new derivatives are lightly regulated and a source of speculative trading strategies. This chapter examines the roles that CFDs have played, either as an accelerant for mispricing was from fundamental values in international equity markets, or as a source of increased market efficiency through the addition of new liquidity. This chapter uses GARCH-based models to test for the impact of CFDs on the return volatility and autocorrelation of the underlying security. In the case of Australia, the same analysis is applied to the individual securities and in the other fifteen countries investigated the analysis is applied at the level of the market index (due to data limitations). The chapter also investigates whether the stylised characteristics of CFDs are more or less pronounced in low liquidity exchanges. This chapter finds that CFDs appear to have lowered asset-specific variance and increased return autocorrelation. Some tentative explanations for these findings are offered in conclusion. The presence of bid and ask price 'overhangs' associated with CFD trading cannot be rejected and may be associated with EGARCH-volatility reductions found in some jurisdictions.*

2.1. Introduction

The CFD industry grew significantly from the product's creation in the mid-1990s until the onset of financial crisis in 2007. Due to the role of these products as a method of quickly entering and exiting markets, they are attractive to risk loving investors seeking to maximize leverage. Investors can open positions, either long or short[26], using CFDs, with leverage sometimes as low as 1%, but the standard rate is 10% throughout the industry. This means that the position can theoretically be one hundred times larger than the amount of capital the investor initially possesses. The nature of these leveraged investors could potentially affect the behaviour of the exchange as a whole. Alternatively, CFDs may have a beneficial impact on exchanges worldwide due to the added liquidity the products' leverage provides. It must be noted that some exchanges, such as the Irish Stock Exchange (ISEQ Index), would have had minimal exposure to leveraged products prior to the arrival of CFDs. The CFD industry remains understudied, un-transparent and lightly regulated in comparison to other derivatives

[26] Buying a product 'long' is the process of buying a financial product or the intention of an investor to profit from the price of the product increasing. Alternatively, buying a product 'short' is the process of selling a financial product or the intention of an investor to profit from the price of the product decreasing

exchanges such as the options and futures markets. This chapter intends to answer some of the outstanding questions that have been asked about the CFD industry.

The main question is whether CFDs have increased excess volatility in international exchanges. Alternatively or in addition, has this same leveraged investment increased exchange efficiency through liquidity improvements? Also, are these effects, either positive or negative, amplified on low liquidity exchanges? Due to low volumes traded on some smaller exchanges the added volumes from leveraged trading may amplify any effect that CFDs have on international exchanges. Additionally, what are the true levels of CFD volumes traded internationally? Finally, did the ASX CFD decision to segregate CFDs on a separate exchange increase or reduce the volatility of the main ASX exchange?

As a solution to the problem of CFD-specific trading volumes being unavailable for sixteen of the jurisdictions investigated, the daily returns of the main domestic indices are used in the international GARCH and EGARCH models. In contrast, the Australian Securities Exchange (ASX) provides a dataset explicitly offering daily and weekly flows of CFD volumes which allows for a more in-depth analysis of the secondary hypotheses based on the arrival and withdrawal of CFDs. This will be discussed in section 2.4.2. The ASX individual equity database allows for a specific investigation of the CFD investor's holdings after the creation of the ASX CFD exchange.

Smith New Court plc. who specialised in the research, origination and trading of equity, developed CFDs in the early 1990s as a method of shorting financial markets. These derivatives were characterised by high leverage, low margins and tax-free profit. They were bought by Merrill Lynch in July 1995 for £526 million. CFDs were institutionally traded from the early 1990's until mid-1998 when they became generally available. A period of regulation reduction and United Kingdom government incentives to regain tax receipts from tax-haven economies such as Gibraltar and Liechtenstein increased interest in CFDs and their trading volumes increased. In 2002, the product became available in Ireland and Australia and subsequently grew until 2007, by which time CFDs were available on most international exchanges. Estimates of CFD volumes across numerous exchanges vary considerably. In Ireland it has been estimated that volumes were as high as 50% of all ISEQ[27] transactions[28]. Estimates in the United Kingdom in 2007 were produced by the Financial Services Authority (FSA) who found that '*The CFD market in the UK has grown significantly in the last five years. Current estimates suggest that about 30 percent of equity trades are in some way driven by CFD transactions referenced to the underlying shares' (*FSA – CP07|20, 2007).

There have been instances of trading irregularities associated with CFD investment. The report of the Irish Banking Commission to investigate the systemic banking crisis in Ireland found that an 'overhang' existed from large CFD trades that was capable of leading to confusion and differing interpretations of what was driving the share price collapse of Anglo

[27] The main trading basket of shares on the Irish Stock Exchange is also referred to as the ISEQ 20.
[28] The Sunday Business Post (Ireland) on the 21st of October stated: *'Confidential briefing documents seen by The Sunday Business Post disclosed that the Irish Stock Exchange estimated that CFD trading accounted for up to 50 percent of all its share trading activity', (*Clerkin, 2007)

Irish Bank. In Germany, a report by the ESME[29] in 2009 found that a large unwinding by Porsche of options relating to CFDs in Volkswagen (VW), combined with take-over rumours, had triggered a 500% price increase in less than seven days in late October 2008. These irregularities have attracted increased investigation into CFDs as a tradable product. To counteract these trading anomalies it may be necessary to implement margin-enhancement regulations, or increased taxation on the CFD industry in exchanges where CFDs have been found to have significant negative effects. More drastic action is also a possibility, such as that taken by the Australian Securities Exchange (ASX) in 2007 to ring-fence CFDs within their own separate exchange.

The chapter is organised as follows. Section 2.2 describes the relevant previous literature. Section 2.3 discusses the development of the CFD market, associated international margin levels and the hedging practices of CFD brokers. Section 2.4 provides a detailed account of the data, methodology and structure of the GARCH and EGARCH models. In section 2.5, the results from the GARCH and EGARCH analysis is provided. Section 2.6 offers some explanation regarding the trading techniques used and compares the results. Section 2.7 concludes.

2.2. Previous literature

CFDs alone have received little attention in previous research. There are some papers based on CFDs in the commodity and currency markets, but they only explain the regulatory events imposed by the Australian Securities Exchange (ASX) to mitigate the effects of CFDs. There are no papers currently available that directly investigate the effects that CFDs have had on the individual exchange volatility.

Brown et al. (2009) investigate the ASX's decision to create exchange-traded CFDs. The authors focus specifically on the contract design and the pricing relationship between CFDs and the underlying equity. The authors find that there are other market factors such as competition and close substitutes that will result in the CFD trading at a price close to that of the underlying asset. Bates et al. (2009) examined the regulatory effects of the new disclosure requirements introduced in the United Kingdom in relation to the holding of CFDs. There are numerous papers explaining the dynamics and structure of CFDs, but none of the available literature tests the dynamics of market structure change in the post-CFD introduction era.

CFDs, like other derivative products, allow traders to increase their exposure to an asset, thus amplifying their risk. Some authors believe that destabilising effects are evident in the market as this speculative trading originates from uninformed investors (Cathrath et al., 1995). Some advocates of this view are Figlewski (1981) and Stein (1987). Stein claimed that futures markets attracted uninformed traders because of their high degree of leverage, which can reduce the information content of prices and can cause destabilising market volatility.

[29] The European Securities Markets Expert Group (ESME) was established by the European Commission in March 2006 to provide legal and economic advice on the application of the EU Securities Directives. The ESME suspended its activities in December 2009.

Other papers that support the view that derivative introduction increased spot market volatility include Jeanneau and Micu (2003), Gulen and Mayhew (2000) investigating the United States and Japan, Antoniou and Holmes (2003), Bessembinder and Seguin (1992) and Lee and Ohk (1992). Pok and Poshakwale (2004) and Ryoo and Smith (2004) found similar volatility increases, but also noted greater sensitivity of spot market prices to new information and efficiency improvements through faster information transfers.

Others argue that the introduction of derivatives reduces spot market volatility and in fact stabilises the market. Derivatives can be an efficient medium of price discovery. Other noted benefits include improved market depth, a reduction in market asymmetries, and less cash market volatility as found by Kumar et al. (1995) and Antoniou et al. (1998). Other papers that found volatility reductions after the inclusion of their investigated derivative products include Drimbetas et al. (2007), Bologna and Cavallo (2002), Pilar and Rafael (2002), and Damodaran and Lim (1991).

Another branch of research based on the link between derivative introduction and volatility change found either no correlation whatsoever or a lack of significant results. This included the work of Shenbagaraman (2003) who also found changes in the nature of volatility itself, Mayhew (2000), Darrat and Rahman (1995), Choi and Subrahmanyam (1994), Kamara, Miller and Siegel (1992), Chatrath et al. (2003) and Kan (1997).

Other aspects of previous research based on the introduction of new derivatives are based specifically on the areas of changes in market structure, efficiency and market regulation. Powers (1970) and Danthine (1978) show that futures markets improve overall market depth and the availability of information. Schwartz and Laatsche (1991) and Stoll and Whaley (1988) also found evidence of structural improvements in markets after the introduction of futures. Watt, Yadav and Draper (1992) found no change in volatility post-futures, but did find evidence of efficiency benefits. Santoni (1987), Becketti and Roberts (1990) and Darrat, Rahman and Zhong (2002) all find no volatility changes in the period post-derivatives and in a regulatory response and state that any action to counter non-existent changes would be unwarranted or misguided. Regulatory changes are judged only as necessary where there is a clear causation between the source and the problem.

2.3. CFD markets, margin levels and CFD provider hedging practices

There are many different rules and regulations governing international margin requirements. The United States has implemented a minimum requirement of 50% on all margin levels since the 1970’s. Table 2.1 below shows the differing margin requirements across international exchanges. Table 2.2 represents the sources of the data used in this analysis, along with the sources of estimation date used for the dummy variables in the GARCH models used at the index level. This was completed using a combination of methodologies that include identifying the introduction of the first CFD company offering a tradable product on the investigated exchange, to profit and loss investigations of the primary CFD brokers within a region. The data source for each investigated jurisdiction is also listed.

Table 2.1: *Minimum initial margin requirements by country*

Country	Minimum Initial Margin Requirement (%)[30] by Exchange
United States	50% (Defined in Regulation T[31]) CFDs not allowed due to exchange rules. Though CFD investment on US stocks is available to non-US citizens, who reside outside the US. 10% available to non-residents.
Canada	30% (if allowed by the IDA[32]) 100% otherwise. 10% available to non-residents.
United Kingdom	10% (Possible to get 5% in some brokers)
Australia	5% for high cap[33] on Exchange Traded CFDs, 10% for all others
Others	10% is normal level, but possible to get any chosen level between 1% and 50%

Notes: The data in table 2.1 is taken from the individual trading brochures of each of the exchanges investigated. It represents the required minimum proportionate investment that must be provided in each jurisdiction. Only the major financial centres are quoted here, but the other nations in this investigation are simply denoted as 'others' and generally 10% leverage is commonplace.

Table 2.2: *International exchanges under investigation and methodology to calculate dummy variable*

Country	Exchange	Month of inception of CFDs	Dummy variable identification methodology***	Data source*
Japan	Nikkei 225	December 2004	International broker advertisement	Bloomberg
United States	S&P500	March 2001**	International broker advertisement	Bloomberg
China**	SSE 50	December 2004	International broker brochure	Datastream
Thailand**	SET 50	October 2007	International broker advertisement	Datastream
South Africa	JSE 40	January 2001	International broker brochure	Datastream
United States	Dow Jones 30	March 2001**	International broker advertisement	Bloomberg
Canada	TSX 60	January 2005	International broker advertisement	Bloomberg
United Kingdom	FTSE 100	June 1998	P&L**** of domestic broker	Bloomberg
Norway	OBX 25	July 2005	International broker advertisement	Datastream
Australia	ASX 200	July 2002	International broker advertisement	Datastream / ASX website
Korea**	KOSPI 50	April 2006	International broker brochure	Datastream
Germany	Dax 30	August 2006	P&L**** of domestic broker	Bloomberg
Spain**	IBEX 35	April 2006	International broker advertisement	Bloomberg
Italy	FTSE MIB 40	April 2006	International broker brochure	Datastream
New Zealand	NZ 15	June 2005	International broker advertisement	Datastream
Ireland	ISEQ 20	October 2002	P&L**** of domestic broker	Bloomberg

Notes: *Data sources differ based on attempts to maximise the period under observation – differing providers had different historic availability. **The listed broker advertisements were located online or through historic newspaper article research.. ***Due to Regulation T, CFDs are unable to be traded internally by US citizens. The best estimate of the introduction of CFDs is when they started to trade with the leading international brokers. ****Profit and loss investigation completed using FAME database.

[30] This is measured by a survey of the largest CFD providers worldwide. The names of these companies will remain anonymous throughout this paper as we do not wish to compare spreads between companies in a competitive nature. Company specific data has been collected and held by the author and will not be published.

[31] Regulation T (12 CFR §220 - Code of Federal Regulations) governs the extension of credit by securities brokers and dealers in the United States. It is best known as a control function of margin requirements for stocks bought through leveraged products. The initial margin requirement for stocks in the US is 50% and has been so since 1974. Regulation T gives the Federal Reserve the right to change the initial margin requirement at any time it chooses to do so.

[32] IDA: Investment Dealers Association of Canada. The IDA is connected to the IIROC, which is the Investment Industry Organisation of Canada

[33] Capitalisation rate (or "cap rate") is the ratio between the net operating income produced by an asset and its capital cost (the original price paid to buy the asset) or alternatively its current market value. It is calculated as the ratio of the net operating income of the asset, divided by the cost or present value of the same asset.

Table 2.3 shows the markets investigated in terms of their size, defined as the market capitalisation of the exchange on which they were available. It must also be noted that even with different margin requirements, the companies who provide margined products such as CFDs also have different internal rules to protect themselves. Some of the larger companies provide margin levels of 10% on most European Exchanges, currency and commodity markets such as oil and gold. Some exchange rules are also in place, such as implementing 100% margin requirements on stocks that have a market capitalisation less than a certain threshold, or if their price drops below a certain level. These rules were implemented with great speed in the financial collapse of 2008-2010, where the market capitalisation and share prices of financial institutions plummeted. Brokers placed the margin levels on some of these companies back to 100% in an effort to stem the tide of margined purchasing.

Table 2.3: *International exchanges under investigation*

Country	Exchange and state of capitalisation	International volatility measures**	Market capitalisation. (Billions $)***
Japan	Nikkei 225 – High	SSE, SET	12,880.00
United States	S&P500 –High	FTSE	12,480.00
China*	SSE 50 – High	Nikkei, SET	12,160.00
Thailand*	SET 50 – High	KOSPI, ASX	8,397.15
South Africa	JSE 40 – High	ASX, Nikkei	4,407.24
United States	Dow Jones 30 – High	DAX	3,799.58
Canada	TSX 60 – High	Dow Jones	1,729.39
United Kingdom	FTSE 100 – High	Dax	1,698.13
Norway	OBX 25 – Low	DAX, FTSE	1,511.45
Australia	ASX 200 – Low	Nikkei, NZ	1,224.96
Korea*	KOSPI 50 – Low	SSE, Nikkei	1,171.31
Germany	Dax 30 – Low	FTSE	781.70
Spain*	IBEX 35 – Low	Dax, FTSE	498.36
Italy	FTSE MIB 40 – Low	Dax	382.93
New Zealand	NZ 15 – Low	ASX	276.43
Ireland	ISEQ 20 – Low	FTSE, DAX	50.61

Notes: *No Over-The-Counter Exchange or internal CFD provider. CFD investment is arriving from abroad. It is possible for domestic customers to invest through companies in foreign countries. **The Measure of International Volatility is chosen as the exchange that offers the explanatory significance to the GARCH and EGARCH analysis. ***Market capitalisation rates correct as of June 2011. This is representative of the values at this time of the individual exchange components investigated. Though frequently adjusted, the current value is taken as a best estimate of the division between the high and low market capitalisation exchanges in this investigation. The market capitalisation values are sourced from Bloomberg.

By placing a 100% margin, the brokers also restricted bad debts from clients, who would not be able to quickly respond to margin calls, thus creating the hazard of becoming debtors to the broker with one sharp negative (or positive if the investor is short) market move. Similar rules have been implemented in other periods of great volatility, such as the 12.15pm to 12.45pm time period when the European Central Bank and the Bank of England interest rates are being announced. It is in this time period where equity and currency volatility can change quickly. Also, the time of 2.30pm (East Coast US time) on Fridays is very volatile in the oil market[34], as 'pits close[35]' on the CBOT[36] prior to the weekend. It is not unusual to see the bid

[34] The two biggest world oil markets are the markets for West Texas Intermediate Oil and Brent Crude.
[35] 'Pit Close' is referred to as the close of the trading pit in 'open-cry' markets.

price or the ask price[37] completely disappearing as traders fight to increase or decrease their positions for the weekend.

The most common margin level offered by brokers is 10%, as found on nearly all liquid European markets. Even though some exchanges have laws governing the amount of margin that can be used on their exchange, such as Regulation T[38] in the United States, it is common practice to see US and Canadian equities being offered in Europe and Asia/Pacific with 10% margin by spread-betting and CFD providers because they fall outside the US jurisdiction.

Regulations differ worldwide based on the industry norms that vary across jurisdictions. Brokers sometimes take a trade as a 'bet' and also create a situation where there is no market volatility whatsoever when they accept the trade from their clients but do not buy the physical asset. In this situation, the broker is simply becoming a secondary market maker[39], simply betting against clients and returning a profit. The company also locks in profits by creating an artificial spread between the buying and selling prices of its clients. This secondary market is private, very opaque and also appears to only lightly and locally regulated and documented.

In November 2007 a new phenomenon occurred when CFDs became exchange traded[40] in Australia for the first time. The investor could now see a CFD market on its own and still trade CFDs with the same benefits of leverage from low margin requirements. Because the CFD in Ireland is not exchange traded, it is capable of more directly impacting the primary market as CFD volumes traded are not differentiated from normal exchange activity. In Australia, counterparty risk is also minimized as the settlements of all obligations are guaranteed by the SFECC[41]. The Australian Securities Exchange (ASX) is responsible for maintaining that this new market remains transparent, fair and orderly. They also maintain consistency in the exchange by providing only one standardized contract. The transparency of the market as a whole is fully recorded and documented.

Some alternative, more cost efficient methods to mitigate the potential effects CFDs have include increasing the margin levels that some brokers offer. This means that investors will have to produce more cash as a proportion of their investment, thus reducing the volume of shares that they can purchase. This may result in a situation where investors' assume less risk, thus making the market itself less risky. Another method is to impose a tax or charge on the profits that CFD traders make. This can also be imposed on the broker. Another simple

[36] The Chicago Board of Trade (CBOT), established in 1848, is the world's oldest futures and options exchange. More than 50 different options and futures contracts are traded by over 3,600 CBOT members through open outcry and electronic trading. Volumes at the exchange in 2003 were a record breaking 454 million contracts. On 12 July 2007, the CBOT merged with the CME under the CME Group holding company and ceased to exist as an independent entity.

[37] The bid price is the price at which a trader buys any asset and the ask price is the price at which a trader sells any asset.

[38] Regulation T governs the extension of credit by securities brokers and dealers in the United States. Its best-known function is the control of margin requirements for stocks bought on margin. The initial margin requirement for such margin stock purchases is 50%, and has been since 1974, but Regulation T gives the Federal Reserve the authority to change that percentage. Raising the margin requirement ostensibly reduces risk in the financial system by reducing the potential leverage and total buying power of investors.

[39] A market maker is a company, or an individual, that quotes both a buy and a sell price in a financial instrument or commodity held in inventory, hoping to make a profit on the bid/offer spread.

[40] Exchange traded refers to any financial product that is traded through an exchange. This can be through many different methods such as physical trading or electronic trading.

[41] SFE Clearing Corporation is an organization associated with an exchange to handle the confirmation; settlement and delivery of transactions, fulfilling the main obligation of ensuring transactions are made in a prompt and efficient manner.

method is to place a limit on the maximum amount of CFDs one particular client can buy on one particular day. This would stop investors amassing large positions on volatile days in an attempt to quickly profit by offloading the position. This would also suit longer term investors who use CFDs, who would then build their positions over a period of time rather than buying all their position in one purchase. Any of these options, or even a combination of the stated option would reduce short-term volatility, while simultaneously keeping most of the longer term reduced volatility benefits.

2.4. Data, methodology and structure of the models

2.4.1. An estimate of CFD volumes traded

To test the impact of CFDs on individual markets, one would need to have all available CFD volume data, but unfortunately this is unavailable for the countries being tested[42]. The establishment of the ASX CFD[43] exchange offered a fully transparent dataset, capable of shedding light on the dynamics of CFD markets. With this data, one can investigate the proportion of total volume traded by CFD companies hedging their positions after making trades for clients. Though this may not be representative of country specific characteristics, it may offer insight into volume growth and changes in the moments of price and volume changes. Using the data available from the ASX we can calculate exactly how much of the total volume on the normal spot market is inclusive of CFDs. The results of this analysis are seen in section 2.5.1. The ASX CFD volumes are simply divided by the individual equity volumes per day. The quarterly results are displayed in tables 2.4 and 2.5.

2.4.2. Models of the ASX prior and post ASX CFD division and international indices investigation

The aim of the GARCH and EGARCH investigation is to study the behaviour of volatility in the ASX after the decision to ring-fence CFDs into a separate exchange (the ASX CFD exchange). Two arguments have been forwarded by both advocates and antagonists of the decision alike. Supporters of the decision argue that ring-fencing CFDs has withdrawn most pure speculative trading from the exchange, which may reduce the volatility of the market as a whole (FSA, 2007). We must remember that CFDs are not appropriate as a long-term investment mechanism due to the commissions and overnight interest charges attached. If being used as a long term investment method, these charges would significantly diminish returns, or force the trader to seek higher returns. Therefore, CFDs are suited to more short term speculative investment. This style of investment has been associated with ‘noise trading’ also viewed as high frequency trading which has been found to increase market volatility (Brown, 1999).

[42] All other data in this research is provided by Thompson Reuters Datastream, Bloomberg and finance.yahoo.com and the main econometric software programme used is Stata 11.0. the daily return data for the international exchanges investigated is adjusted for stock splits. All data for our investigation of the ASX is taken from the Australian Securities Exchange website.
[43] Australian Securities Exchange Contracts for Difference

The alternative argument is that ring-fencing the exchange has increased volatility due to a reduction of market liquidity. This can simply be explained by the absence of leverage, which can lead to less shares being traded on an exchange. This reduction of trading volume can cause the speed of transfer of information on the market to fall, thus amplifying natural market movements based on news and investor sentiment (Hendershott and Moulton, 2011). Individual equity movements become more volatile on a daily basis, thus increasing the volatility of the overall exchange. It must also be noted that there is a volatility reducing factor associated with the segregation of CFDs known as the bid and ask price 'overhang' (Report of the Commission of Investigation into the Irish Banking Collapse, 2011). This phenomenon occurs when a significantly larger volume (than that of the average) is placed on either the bid or ask price. The traded price of equity is now dominated by this position and can sometimes freeze until action is taken by the position's owner. The market can therefore show reduced volatility, simply because of a reduction in trading and price movement.

If CFD trading is found to have a volatility increasing effect on exchanges, two of the common methods to help reduce the impact will be to, first, increase margin requirements on CFD trading, thus reducing the amount of volume that CFD traders' trade and, second, to complete a similar operation to the Australian Securities Exchange and ring-fence CFD trading into a separate transparent exchange.

The daily return is calculated as $R_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)$. The dataset is based on the ASX50, which comprises of the 50 largest equities on the ASX exchange. Dividends in this model are ignored for simplicity, but the daily returns are adjusted for stock splits. In a similar manner to Pilar and Rafael (2002), two models of the ARCH family will be used, the GARCH(1,1) model and the EGARCH (1,1). These models will include a dummy variable to signal the division of the ASX CFD exchange, denoted as zero prior, and one thereafter. Results will be inferred from the coefficient of the dummy term, and from the error terms. To mitigate the effects of the subprime crisis which occurred just after the division, the model also includes excess returns of the ASX 200 indices. The most significant indices mitigating international crises effects are used in the international investigation in section 2.5.4. As a proxy of international market volatility, we have chosen to use the Standard & Poor 500[44]. Similarly Bologna and Cavallo (2002) used a GARCH model to test the introduction of futures on the volatility in the Italian Stock Exchange. GARCH models are used to segregate the explicit volatility changes based on the data or theory being tested. To mitigate the effects of international markets, they included the returns of major international exchanges as independent variables. International exchanges that proved to be of no benefit or of no significance to the regression were dropped. One can use similar models to investigate structural changes in all exchanges in this paper.

The main CFD providers entered the Australian market in July 2002. The ASX CFD exchange began trading in November 2007. In a similar manner to Bologna and Cavallo, a

[44] The S&P 500 is a free-float capitalisation-weighted index published since 1957 of the prices of 500 large-cap common stocks actively traded in the United States. The stocks included in the S&P 500 are those of large publicly held companies that trade on either of the two largest American stock market companies; the NYSE Euronext and the NASDAQ OMX.

dummy variable has been included to denote the addition of CFDs in the ASX. There will be three time periods of investigation, with three separate regressions denoting the different states of the exchange. The first is prior to the arrival of CFDs, the second is when CFDs are present and the third is after the ASX CFD exchange is established. Some issues were considered when determining the date of the dummy variable. The possibility that the market reaction occurred when the news first broke that CFDs would be available was considered. But gauging an adequate representation of this data was scientifically implausible despite numerous attempts. The date of CFD origination was found to be the most adequate assumption to be used when determining the dummy variable switching date.

The GARCH model was developed by Bollerslev (1986) from the ARCH[45] model previously introduced by Engle (1982). The GARCH (p,q) model suggested by Bollerslev is represented as:

$$R_t = bx_t + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t),$$

$$h_t = x_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j},$$

where ε_t is asset-specific returns and x_t are other explanatory variables included in the GARCH equation. If q=0, the process reduces to an ARCH(p) process and for p=q=0, ε_t is just white noise. The GARCH(1,1) framework has been extensively found to be a parsimonious representation of asset-specific variance that fits well and therefore is adequate to use with many financial time series (Bollerslev, 1987). One of the appealing characteristics of GARCH is the capturing of volatility clustering[46]. The model used in this paper to investigate volatility changes after CFD introduction is:

$$R_t = b_0 + b_1 R_{t-1} + b_2 R_{NIKKEI_t} + b_3 R_{FTSE_t} + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \text{ and } \alpha_i, \beta_j \geq 0,$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma D_{CFD_t},$$

where $\gamma \geq 0$ in addition to the other non-negativity restrictions above. Thus the value of the variance scaling parameter h_t, now depends on past values of the shocks, which are captured in the lagged squared residual terms, and on past values of itself, which are captured in the lagged h_{t-1} term. h_t is known at the beginning of time t. Ω_{t-1} is the information set at the end of time period t-1. R_{NIKKEI_t} represents the daily return on the NIKKEI and R_{FTSE_t} represents the daily return on the FTSE. These variables are included in the mean equation to

[45] AutoRegressive Conditional Heteroskedasticity (ARCH) models are used to characterize and model observed time series. They are used whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size, or variance. In particular ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the previous innovations.

[46] Volatility clustering refers to the observation, as noted by Mandelbrot (1963), that 'large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes'.

mitigate the GARCH model against international effects. D_{CFD_t} is included in the variance equation as a representation of the dummy variable included in the GARCH model denoting the arrival of CFDs. This variable takes a value of zero prior to the arrival of CFDs and one thereafter. With GARCH the conditional variance is modelled as a linear function of the lagged conditional variance in addition to the past error variances contained in the ARCH representations. Individual regressions have also been completed for each equity in the CFD exchange and for an evenly weighted basket representative of exchange wide returns. There are 50 equities with CFD counterparts on the ASX CFD. One can use GARCH to test for changes in volatility after the inclusion of CFDs in the exchanges investigated and also use EGARCH regressions on the international exchanges. Similar EGARCH models were also applied to the individual equities on the ASX to investigate micro-market structural changes. Adding a dummy variable to investigate CFD inclusion created issues for some of the GARCH models used earlier, but using EGARCH offered a solution to this problem. In these cases, due to problems with low liquidity in the exchange being investigated, the output from the GARCH models contained negative constants and explosive GARCH coefficients. This problem did not occur when EGARCH was used.

The Exponential GARCH model (EGARCH) was first developed by Nelson (1991). The ARCH(p) and GARCH (p,q) models impose symmetry on the conditional variance structure which may not be appropriate for modelling and forecasting stock return volatility. EGARCH models capture the most important stylised features of equity return volatility, namely time-series clustering, negative correlations with returns, log-normality and with other certain specifications, long memory (Brandt and Jones, 2006). Nelson (1991) proposed the exponential GARCH or EGARCH model as a method of dealing with the problem. Under the EGARCH(1,1) framework, the conditional log variance is calculated as:

$$R_t = bx_t + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t),$$

$$\log(h_t) = \omega + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + \beta \log(h_{t-1}) + \delta \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}.$$

The parameters ω, α, β and δ are constant. The EGARCH model has two distinct advantages over the GARCH model. First, the logarithm construction of the conditional variance equation ensures that the estimated conditional variance is strictly positive, thus the non-negativity constraints used in the estimation of the ARCH and GARCH models are not necessary. Also, the parameter δ typically enters the conditional variance equation with a negative sign, thus bad news, $\varepsilon_t < 0$ generates more volatility than good news. One can test numerous international exchanges to add clarity to the results and for the ASX EGARCH, but only the Nikkei and FTSE added explanatory significance.

In the EGARCH model used, the dependent and independent variables remain similar to those used in the GARCH analysis:

$$R_t = b_0 + b_1 R_{t-1} + b_2 R_{NIKKEI_t} + b_3 R_{FTSE_t} + \varepsilon_{t,}$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t).$$

But the specification of the conditional variance equation now becomes:

$$\log(h_t) = \omega + \alpha \left[\left| \frac{\varepsilon_{t-j}}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right| \right] + \beta \log(h_{t-1}) + \delta \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma D_{CFD_t},$$

where h_t is known at the beginning of time t. Ω_{t-1} is the information set at the end of time period t-1. This makes the leverage effect exponential instead of quadratic and therefore, estimates of the conditional variance are guaranteed to be non-negative. The EGARCH model allows for the testing of asymmetries, which is picked up in the β term. Similarly to the GARCH model, R_{NIKKEI_t} represents the daily return on the NIKKEI and R_{FTSE_t} represents the daily return on the FTSE. These variables are included in the mean equation to mitigate the EGARCH model against international effects. D_{CFD_t} is included in the variance equation as a representation of the dummy variable included in the EGARCH model denoting the arrival of CFDs. This variable takes a value of zero prior to the arrival of CFDs and one thereafter. When $\beta = 0$, the model is symmetric, but when β <0, then positive shocks generate less volatility than negative shocks. The model captures the asymmetric features of the dataset, which occurs when an unexpected drop in price due to bad news increases volatility more than an unexpected increase in price because of good news of a similar magnitude. The model expresses the conditional variance of the variables as a non-linear function of its own past variance. When investigating stock indices, Hentschel (1995) found in-sample evidence showing a slight superiority of EGARCH's specification over GARCH due to this asymmetric volatility effect, also known as the leverage effect.

2.5. Results

2.5.1. CFD volumes in the ASX CFD exchange

Even though the ASX CFD exchange is in its relative youth, it offers insight into how much extra volume would be created if CFDs were hedged on the ASX exchange. The results of the firm by firm analysis can be found in tables 2.4 and 2.5 below. The volumes of CFD traded were calculated by breaking the time periods into quarters from February 2008 until March 2010. The CFD traded volumes used are from the Australian Securities Exchange website and are simply segregated by quarter and then by the specific company. The CFDs are then de-leveraged to their fully margined spot market equivalent position holdings, representative of the amount of spot market activity that would have had to have been fully-hedged if a broker was completely mitigating their risk as a CFD provider. Table 2.4 represents the total amount of CFDs traded as a proportion of spot market activity by trading quarters from Q1

2008 until Q1 2010. Table 2.5 replicates the same analysis, but segregates the data by company.

Table 2.4: *Percentage CFD volume as a proportion of total volume (as a percentage (%))*

Percentage CFD volume as a proportion of Total Volume	
Quarter	**Percentage (%)**
Q1 2008	5.08
Q2 2008	7.13
Q3 2008	5.92
Q4 2008	3.61
Q1 2009	8.66
Q2 2009	9.52
Q3 2009	12.39
Q4 2009	14.21
Q1 2010	12.40

Note: The above statistics are associated with the calculations of section 2.5.1, where the CFD volume traded, for each equity on the ASX exchange are divided by the alternative non-CFD volumes. We can clearly see a growing trend in the usage of CFDs in recent times.

We can see from table 2.4 that since the birth of the ASX CFD exchange, 8.83% of the total exchange volume has been traded in CFDs. This also shows a notable increasing trend with a peak of 14.2% in Q4 2009. Looking at individual companies, we find that there are companies that experience over 50% of CFD to exchange volumes. Numerous international estimates place the level of CFD trading at 20-50% (FSA 2007, Clerkin 2007) of total exchange activity (table 2.5), though current ASX market wide levels are between 12-14%. Some reasons for this lower than expected estimate would be the relative youth of the ASX CFD exchange, as spreads are still relatively wide and liquidity is noted as lower than that expected.

2.5.2. EGARCH investigation of the ASX

Segregating CFDs to a separate exchange can justifyably either increase or decrease the volatility of the main equity exchange. Once segregated, one would expect volatility to simply decrease as most of the reputably CFD influenced volatility is now absent. But this is not simply the case, Volatility reductions can also be explained by the presence of an ‘overhang’ on the bid and ask prices of the market. This phenomenon occurs when a significantly larger volume (than that of the average) is placed on either the bid or ask price. The traded price of equity is now dominated by this position and can sometimes freeze until action is taken by the position’s owner. The market can therefore show reduced volatility, simply because of a reduction in trading and price movement. Alternatively, the segregation of CFDs may cause volatility to increase based on the reduction of liquidity. This can be justified by the absence of leverage, therefore reducing the size of the average position. A reduction in liquidity reduces the speed of transfer of information in a market, thus amplifying natural movements based on news and sentiment.

Table 2.5: *ASX CFD volumes as a percentage of total market volumes*

Percentage CFD volume as a proportion of Total Volume (As a Percentage (%))										
Equity	**Q1 2008**	**Q2 2008**	**Q3 2008**	**Q4 2008**	**Q1 2009**	**Q2 2009**	**Q3 2009**	**Q4 2009**	**Q1 2010**	**Average**
Amcor	5.14	4.11	1.57	0.14	14.89	11.67	7.55	7.87	4.22	6.35
Alumina	3.58	2.59	1.67	1.40	1.24	1.00	5.07	3.23	7.20	2.99
AMP	1.62	1.56	2.52	1.22	6.01	9.26	6.80	7.05	6.50	4.72
ANZ	6.76	10.02	5.56	2.54	5.67	6.91	9.96	10.06	7.73	7.24
AXA	7.66	14.69	8.35	3.11	2.45	2.49	3.15	4.16	4.81	56.5
BHP Billiton	8.71	12.86	9.13	5.64	7.28	9.11	12.96	11.74	9.75	9.68
Boral	3.54	3.67	1.45	2.38	5.17	11.33	20.31	29.09	42.21	13.23
Coca Cola	3.46	4.07	6.61	5.17	7.51	7.63	7.62	10.17	16.25	7.61
CSR	5.75	5.01	3.48	0.89	2.37	7.50	22.96	16.40	2.47	7.42
CBA	1.23	2.19	0.60	0.72	15.04	5.66	9.36	4.59	4.11	4.83
CSL	1.10	2.65	15.04	1.58	16.36	5.27	11.79	15.23	27.06	10.67
Fosters	17.58	8.88	6.65	8.21	6.85	19.25	20.30	27.96	11.05	14.08
IAG	0.63	0.65	1.07	0.95	2.64	2.61	4.02	3.44	4.11	2.23
Fairfax	1.20	4.55	1.72	1.56	0.70	11.38	2.68	4.66	2.43	3.43
Lihir Gold	0.80	0.51	1.82	0.16	2.09	15.00	0.86	199	2.36	2.84
MAB	3.07	0.99	0.66	0.64	1.09	1.20	3.81	13.22	4.56	3.24
Newcrest	0.70	3.28	2.29	2.92	12.58	12.40	7.19	7.77	18.27	7.48
News Corp	7.39	27.47	9.63	14.38	13.30	12.22	44.17	72.85	55.36	28.53
Origin	2.21	1.39	10.80	9.92	6.75	14.23	19.01	38.30	22.76	13.93
Oil Search	4.20	1.34	1.44	1.35	11.96	43.64	22.97	23.27	3.93	12.67
Orica	7.68	13.01	22.78	5.79	72.55	19.18	67.49	28.59	37.16	30.47
Onesteel	7.19	17.40	22.36	6.16	7.25	12.03	16.44	20.87	10.51	13.35
Paladin	3.58	4.08	3.10	1.57	6.15	3.17	6.29	11.67	6.52	5.12
QBE Insur.	1.40	3.49	2.56	3.88	0.94	0.86	0.87	2.14	2.23	2.04
Quantas	3.63	3.38	3.90	1.37	0.86	1.80	4.97	2.98	1.20	2.67
Rio Tinto	3.89	39.30	20.46	4.27	3.93	8.31	12.46	19.67	15.87	14.24
Santos	0.90	1.93	2.18	0.81	3.19	3.65	5.22	4.80	3.93	2.95
Suncorp	17.67	10.38	2.76	0.78	3.86	17.47	7.69	13.07	16.31	9.99
Tabcorp	9.12	17.43	19.75	28.08	3.64	11.64	22.86	24.60	38.16	19.47
Toll Holdings	6.09	5.65	8.54	2.37	13.43	28.57	30.44	14.61	8.26	13.10
Transurban	0.99	2.57	3.60	6.44	11.30	19.57	22.30	14.07	23.12	11.55
Telecom Corp.	1.84	1.77	1.68	5.31	8.05	3.79	11.78	20.88	15.09	7.79
Westpac	2.24	4.03	3.17	0.69	2.35	1.65	4.73	9.76	7.60	4.02
Westfield	2.46	3.39	3.05	1.77	1.47	1.09	2.21	4.47	2.93	2.53
Woolworth	2.34	8.53	2.44	1.14	11.61	0.58	10.62	2.18	3.57	4.77
Woodside	30.71	14.58	8.49	1.27	34.73	16.17	13.56	7.17	15.48	15.79
Wesfarmers	3.82	6.95	1.62	0.38	1.60	0.47	7.24	23.51	5.52	5.67
Total	5.08	7.13	5.92	3.61	8.66	9.52	12.93	14.21	12.40	8.83

Note: The data was collected from the Australian Securities exchange at www.asx.au. The results are calculated as the de-leveraged representation of a full margined trading position specific to the company in the stated time period. The result is then divided by the associated spot market trading volumes to offer a representation of approximate CFD exposures on the Australian Securities Exchange (ASX).

The ASX merits further investigation due to it being a special case involving CFDs. CFDs began trading on the ASX in July 2002 through new and improved trading platforms offered by the largest spread-betting and CFD providers. Then, in October 2007, the ASX took the decision to separate CFD trading onto its own separate exchange. This offers three distinct time periods to test differences in the structure of the market. The first period is prior to CFD exposure, between January 1998 and November 2007. This investigates the arrival of CFDs using a dummy variable in the variance equation to test volatility. The dummy variable is zero prior to CFDs and one after CFD-implementation. The second scenario is when CFDs exited the primary market. The period under investigation is from July 2002 until July 2010, again using a dummy variable to test market volatility when CFDs left the market. The third sample selection is the total period, from January 1998 to June 2010, again using a dummy variable taking the form of zero when the market had no CFD exposure and one otherwise. Investigating these regression results offers interesting evidence supporting the view that CFDs in fact reduced long term market volatility from added liquidity benefits. The highest correlated exchanges that offer significance are the Nikkei 225 in Japan and the New Zealand Stock Exchange (NZ15). The pairs are used to mitigate international factors in the EGARCH regressions.

In the total period, it is found that volatility decreased 1.09% after the introduction of CFDs. Investigating the shortened time period around the set introduction date of July 2002 finds that the change in volatility falls slightly to 0.78%. Of further interest is the change in volatility after the ring-fencing of CFDs into their own separate exchange. In the period after the division of the ASX and ASX CFD exchange, volatility increased 3.55% (results for all exchanges investigated are found in table 2.8). This result holds even after mitigating the effects of the fallout of the recent international crisis using the NIKKEI 225 and NZ 15. The results for the inclusion of CFDs are significant at the 10% level, while the withdrawal of CFDs is significant at the 1% level. The results of this analysis can be found in table 2.6 in relation to the individual ASX equities. These findings offer significant evidence that CFDs actually benefitted the ASX by decreasing volatility. CFDs appear to be associated with significant volume increases. For every trade that occurs at a particular price, there must be a counterparty willing to accept the opposing trade. CFDs appear to have increased the probability of finding this counterparty.

Table 2.6: *EGARCH(1,1) results for individual ASX CFD equities*

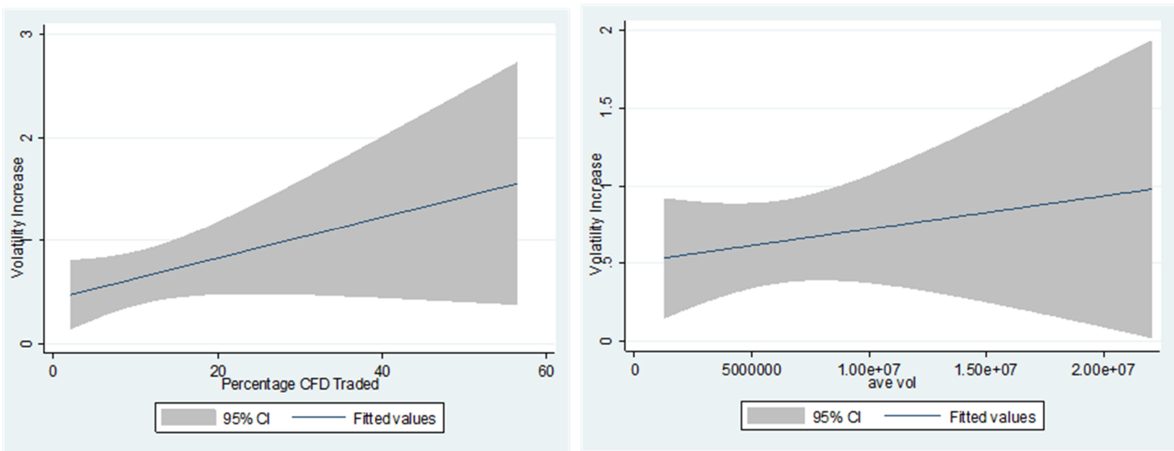
Company	γ coefficient	Company	γ coefficient
Alumina	0.121**	Oil Search	1.223*
Amcor	0.157***	Orica	0.196***
AMP	-0.017**	One Steel	0.056
ANZ	0.919*	QBE	2.285*
AXA	2.447*	Qantas	2.022*
BHP Billiton	0.011	Rio Tinto	0.018
Boral	0.071**	Santos	0.400**
Coca Cola	-0.016***	Suncorp	1.346*
CSR	-0.039*	Tabcorp	1.324*
CBA	0.416**	Toll Holdings	0.592*
CSL	0.042	Transurban	0.183*
Fosters	0.932*	Telecom NZ	-0.009***
IAG	0.719*	Westpac	1.328*
Fairfax	2.583*	Westfield	0.106***
Lihir Gold	0.035	Woolworth	1.197*
Newcrest	0.199	Woodside	0.158***
News Corp	1.396*	Wesfarmers	0.128**
Origin	0.487***		

Note: The above table represents the estimated γ coefficients for each investigated Australian company traded on the ASX CFD exchange using the discussed EGARCH(1,1) methodology to investigate changes in volatility dynamics after CFD introduction. The robust standard errors for each of the γ coefficients are marked in parentheses, where ***p<0.01, **p<0.05 and *p<0.10. The complete results of all the individual EGARCH models can be found in table AI in the Appendices.

2.5.3. EGARCH investigation of the ASX CFD exchanges components

The ASX exchange consists of over two hundred components, yet the ASX CFD exchange only includes the most liquid equities to be traded. On the ASX CFD exchange, there are more than 50 equities included. The ASX CFD exchange also offers commodity and currencies as CFD traded products, but they are outside the scope of this paper. This section investigates the trends of the individual equities traded on the ASX CFD. Only 36 of the 50 available ASX CFD equities possessed a complete dataset. EGARCH models were applied to all of the 50 equities, but due to differing problems such as no liquidity in some periods and companies falling in and out of the sample, only 36 equities are included in the final results, which are displayed above in table 2.5. The company under investigation and the associated gamma coefficients from the EGARCH individual investigations are presented. The dataset is based on the weekly market prices of the individual equities investigated and begins in January 2003, and ends in April 2010. Again this analysis used a dummy variable to signal the withdrawal of CFDs from the normal exchange in October 2007 after the establishment of the ASX CFD exchange. To mitigate internal volatility in Australia, the models have used the ASX200 index as a proxy. To mitigate external effects the S&P500 was used. There was also significant explanatory power found in using the first lag of the individual equity prices. In figure 2.1a, we show a simple linear fit of the estimated γ_i coefficient against the percentage of equity volumes that are CFD traded and the average total nominal volumes traded by specific equity is located in figure 2.1b. The estimated CFD trading volumes as a proportion of total spot market activity is located on a monthly level in table 2.4 and by company in table 2.5. The daily levels are used in the calculation of these simple linear models.

Figure 2.1: *The relationship between volatility, percentage CFD volumes traded (a) and average volume traded (b)*



Note: Figure 2.1 above shows the relationship between the volatility increases in the combined large and small scale samples investigated. The samples are compared to their linked findings of the percentage CFD traded calculations and the average daily traded volumes. The grey regions around the line of best fit represents the 95% confidence intervals associated with the data. We can see a clear positive relationship associated between the two, indicating that the more of the total volumes traded on a particular equity that is CFD traded, then more volatility is associated with this particular days trading. In the second figure we can see a similar, but not as large-scale a relationship between volatility and the more of a particular equity traded on one particular day. The fact that figure 2a is more positive than figure 2b indicates increased volatility stemming from increased CFD trading.

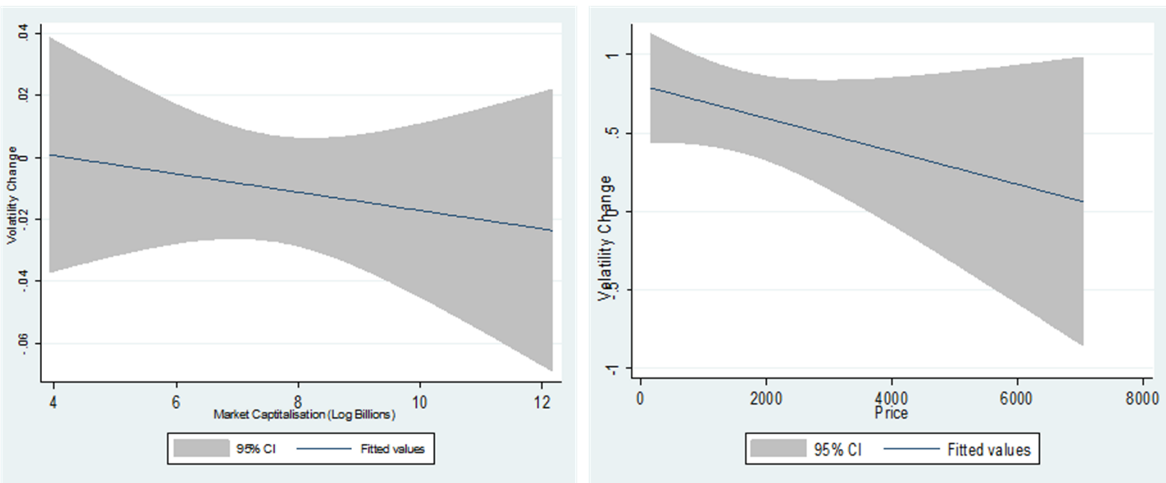
These simple models can be denoted as:

$$\gamma_i = a_0 + b(\%\, CFD\ traded_i) + \varepsilon_i$$
where i = 1, ..., 36

$$\gamma_i = a_0 + b(average\ volume\ traded_i) + \varepsilon_i$$
where i = 1, ..., 36

In 32 of the 36 equities investigated, the volatility of individual equity increased after the segregation of CFDs to the ASX CFD exchange. This again is indicative of reduced liquidity as CFDs were being withdrawn from the exchange. Using the data collected in these regressions, we can further investigate where this added volatility originates. Based on the percentage of volume that is CFD traded in the ASX exchange, we can match the volatility levels found in the EGARCH analysis with the corresponding levels of CFD trading. In figure 2.1a, we see the volatility increases found from the EGARCH investigation. Each observation is then matched with the corresponding percentage of CFD trading volume in the period before the division of the ASX CFD exchange. From this we find a clear positive correlation between the two, indicating that equities with a higher proportion of CFD trading are more susceptible to increased volatility after the withdrawal of CFD investment. In figure 2.1b, we can see the positive correlation between volatility increases after the withdrawal of CFD investment and the average volumes traded. We again see a positive correlation indicating that equities with higher volumes traded are connected with increased volatility when CFD investment was withdrawn.

Figure 2.2: *The relationship between volatility, log market capitalisation (a) and nominal price (b)*



Note: Figure 2.2 investigates the link between the pricing dynamics of CFD traded equities to test for the standard traits of speculative traders. Those who use CFDs are most likely to focus on penny shares due to the minimal cost of purchase, high exposure and relative opportunities for massive payoffs. We can see that smaller market capitalisation companies subjected to CFD investment are subject to more volatility on average than that of their higher capitalisation counterparts. In terms of price, it is found that in Australia, lower nominally priced equities are subject to more volatility stemming from CFD investment. This is because the nominal change of price in larger priced equities is much higher than that of their lower counterparts. In this scenario, a one cent change in a low priced equity can lead to more significant payoffs than a similar nominal move of a higher priced equity. Overall, lower priced shares are more appealing to the traits and characteristics of risk loving investors for which CFDs are a prime investment vehicle.

In figure 2.2a, we show a simple linear fit of the estimated γ_i coefficient against the market capitalisation of the equity being invested in and the nominal price of each equity investigated in figure 2.2b. These simple models can be denoted as:

$$\gamma_i = a_0 + b(log\, market\, capitalisation\, of\, equity_i) + \varepsilon_i$$
where i = 1, ..., 36

$$\gamma_I = a_0 + b(nominal\, price\, of\, equity_i) + \varepsilon_i$$
where i = 1, ..., 36

Figures 2.2a and 2.2b above investigate some of the particular trading characteristics of CFD investment. Both phenomena are connected as market capitalisation tends to be positively associated with price. Those who use CFDs tend to be risk tolerant. Of course equities with high market capitalisation tend to be seen as value investment due to the dividends offered. Alternatively, low market capitalisation equities offer more growth opportunity. There may be a greater tendency for CFD traders to purchase CFDs in low capitalisation equities due to these growth opportunities. CFDs are denominated in cents, thus share X trading for example at €4.56, is denominated as 456 cents. This allows CFD traders and spread-betters alike to make their trades as 'bets'. If the investor is making the bet at 10% margin, and has €1,000 he/she will therefore be long or short €21.90 per-cent price move. Therefore, after a 46 cent share price reduction, the bet will have lost all of the starting investment.

There is an observed tendency for CFD investors to purchase equities with a low nominal share price. Take for example share Y, trading at €0.65 and an investor with €1,000 to invest. The investor is capable of going long or short €153.84 per point move. The brokers must also hedge themselves from the risk of this trade, and to become 100% hedged, they must buy 220 units of share X or 1539 units of share Y. If the share prices of both X and Y fall, brokers wishing to minimise their own hedging risk will increase the margins available on the stocks that they offer to clients. It must also be noted that higher volatility will of course be found in higher percentage price changes from lower equity prices, but this effect is constant throughout both periods, as low share prices continue to be low and high prices have fallen to lower levels in the midst of the fallout from the current international crisis.

2.5.4. EGARCH investigation of international volatility effects stemming from CFDs

Now we extend the analysis to other international markets, and indices rather than the individual equities. We use the same GARCH and EGARCH models denoted earlier, but now CFD_x is indicative of when CFDs were introduced in each specific international exchange. Table 2.2 denotes the estimated starting points of CFD trading in numerous international exchanges. This provides a date for which a dummy variable could be used in the international EGARCH investigation. As explained in section 2.4.2, this date was chosen as the dummy switching date despite numerous other hypotheses being investigated. Deciphering the associated switching date for the dummy variable used was completed through a thorough investigation of the relevant company-specific documents (such as advertisement campaigns, regulation applications, etc.). Also, where available, the first profit and loss accounts are used as a representation of the provision of CFDs by these companies to clients based on the underlying international indices investigated. Using a combination of these techniques provided an estimated date for the first signs of CFD provision. The result of this analysis was displayed in table 2.2 earlier in the chapter.

In table 2.7 (with a more descriptive analysis of the results in table AII of the Appendices), an EGARCH model based on volatility changes was completed across numerous international exchanges with the estimated starting point of CFD trading used as the dummy variable change-over point. Using these dummy variables to signal the reported commencement of CFD trading in each exchange investigated we estimate values of γ and explain the results. Unlike the ASX scenario in Australia (investigated separately in table 2.8), no other exchange investigated has gone through the process of withdrawing CFD investment. Instead, all have only added CFDs as a new form of investment. The dummy variable therefore takes the value of zero for the period prior to the introduction of CFDs and one thereafter. A non-zero coefficient on the variance equation is again indicative of a rise in volatility, while a negative value indicates a decrease in volatility. The results indicate that 13 of the 16 exchanges investigated show reduced volatility in the period after the introduction of CFDs. Similarly eight of these thirteen exchanges are significant at the 1% level with two of the three exchanges in which increased volatility being similarly significant at the 1% level. The average volatility reduction across all exchanges investigated is 1.76%.

2.5.5. GARCH volatility investigation of the exchanges under investigation

Including dummy variables in the EGARCH analysis increases the risk of modelling failure. This may arrive in the form of negative constants, explosive GARCH coefficients, or simply, insignificant results. One of the best methods to counteract this problem was to simply divide the investigation into two sections and investigate changes in the GARCH coefficients which can be found in table AIII of the appendices. Using two GARCH (1,1) models, one for the time period before the introduction of CFDs and one for the period after, dynamic changes in the coefficients of the GARCH analysis can be investigated. From this we can obtain more information about the introduction of CFDs in the exchanges investigated. We can then estimate α_i and β_i for the pre-CFD period and α_i^* and β_i^* for the post-CFD period to investigate changes.

Stata 11.0 is used as the primary econometric package. Investigating the coefficients offers interesting results. The GARCH methodology is applied to each of the investigated indices, with the values of $\beta_2 Rx_t$ and $\beta_3 Ry_t$ (The variables included in the mean equation to represent international effects on the GARCH model, with x_t and y_t representing the included exchanges) changing by exchange based on explanatory significance of the associated alternative indices used in the GARCH analysis. These statistics were chosen to mitigate the effects of international crises as used by Bologna and Cavallo (2002).

We begin by investigating the change in the persistence of shocks from the pre-CFD and post-CFD periods which is simply measured as $((\alpha_1 + \beta_1) - (\alpha_1^* + \beta_1^*))$. A negative value for this statistic might be interpreted as an increase in market efficiency or market resilience, since the persistence of volatility shocks declines. The persistence change is negative in nine of the fifteen exchanges investigated. The second factor investigated is the difference between b_1 and b_1^*, where a negative value indicates a decrease in the autoregressive effect of returns, indicating that the market has increased its efficiency in the weak sense as proposed by Booth and Fama (1970). Twelve of the fifteen exchanges show a decrease in the autoregressive effect of returns. The final metric investigated is based on asset-specific variance. We know that when the sum of α_1 and β_1 is less than one, the model has finite asset-specific variance h which can be found by setting $E[\varepsilon_{t-1}^2] = h_t = h_{t-1} = h_0$. We can solve for $h_0 = \frac{\alpha_0}{1-\alpha_1-\beta_1}$. To find the change in asset-specific variance between the pre and post-CFD introduction period, we simply calculate h_0-h_0^*, with $h_0^* = \frac{\alpha_0^*}{1-\alpha_1^*-\beta_1^*}$. In twelve of the exchanges investigated between January 1998 and December 2010 in table 2.9, we can see a weak-form of improvement in market efficiency. The DAX (Germany), MIB (Italy) and Nikkei (Japan) showed a combined efficiency decrease as found by the three measures. Alternatively, seven of the exchanges showed significant efficiency improvement after CFD introduction.

Table 2.7: *EGARCH (1, 1) results for international exchanges*

Exchange	b_0	b_1	b_2	b_3	ω	α	δ	β	γ **(t-stat)**	**Log-L**
Dow Jones	0.009076	-0.125785	0.3338351		0.000474	-0.0831642	0.1402135	0.9819005	**-0.0059511**	-6327.740
(DJIA)	(0.90)	(-9.81)*	(46.85)*		(0.94)	(-13.67)*	(17.73)*	(474.99)*	**(-2.71)****	
S&P 500	0.005394	-0.133584	0.427768		0.000137	-0.087054	0.12869	0.9838123	**-0.0032459**	-6428.531
	(1.24)	(-10.10)*	(45.56)*		(1.56)	(-14.52)*	(14.11)*	(579.20)*	**(-1.63)**	
FTSE 100	0.0056275	-0.041872	0.5341776		0.0003572	-0.0479366	0.1506751	0.9900448	**-0.0046357**	-5404.856
	(0.69)	(-4.91)*	(94.90)*		(0.94)	(-8.58)*	(16.12)*	(559.22)*	**(-2.21)*****	
Germany	0.0196417	0.0058772	0.9842521		0.0023139	-0.032744	0.1686686	0.9913479	**-0.0031227**	-3993.507
(DAX)	(1.70)	(0.64)	(108.56)*		(1.22)	(-4.44)*	(16.90)*	(459.12)*	**(-0.91)**	
Canada	0.0207312	0.0124458	0.6224235		0.0025697	-0.0370676	0.1477299	0.9914062	**-0.0001979**	-4064.86
(TSX)	(1.61)	(0.92)	(52.04)*		(1.56)	(-5.12)*	(17.82)*	(622.65)*	**(-1.41)**	
Spain	0.0041875	0.0192806	0.4493877	0.4371921	0.0021347	-0.0148918	0.1723977	0.9929173	**+0.0019182**	-3456.841
(IBEX)	(0.40)	(2.47)***	(38.33)*	(28.71)*	(1.15)	(-2.79)**	(21.33)*	(590.41)*	**(0.63)**	
China	0.0098584	0.0144379	0.0676526	0.0575277	0.0227771	-0.0329696	0.1496995	0.9749913	**+0.0179002**	-5810.724
(SSE)	(0.74)	(0.87)	(4.09)*	(5.00)*	(8.74)*	(-6.17)*	(22.86)*	(347.35)*	**(6.37)***	
Japan	0.0343495	-0.029504	0.0589045	0.3581273	0.0150057	-0.062914	0.1500313	0.9796215	**-0.008329**	-5200.813
(Nikkei)	(1.87)	(-1.83)	(5.46)*	(38.99)*	(4.75)*	(-8.31)*	(11.17)*	(300.10)*	**(-2.19)*****	
Australia	0.02046	-0.07567	0.2425	0.33842	0.008487	-0.07711	0.11819	0.97986	**-0.010955**	-3395.23
(ASX)	(1.88)	(-5.28)*	(30.25)*	(22.01)*	(2.96)**	(-8.96)*	(8.62)*	(255.54)*	**(-2.71)****	
Ireland	0.007338	0.0750703	0.5869988	0.1166594	0.012622	-0.0355419	0.1270174	0.9867728	**-0.0059113**	-4776.872
(ISEQ)	(0.45)	(5.53)*	(26.19)*	(6.46)*	(6.89)*	(-5.27)*	(13.91)*	(646.50)*	**(-2.90)****	
South Africa	0.0420208	-0.017971	0.1260832	0.4065182	0.0132082	-0.0561115	0.1409091	0.9805461	**-0.0080162**	-4888.518
(JSE)	(2.44)***	(-1.09)	(8.56)*	(18.79)*	(3.88)*	(-8.78)*	(12.01)*	(278.35)*	**(-2.30)*****	
Italy	0.0130309	-0.007421	0.7046277		0.0006968	-0.029181	0.2346792	0.9835783	**-0.0022985**	-3415.462
(FTSE MIB)	(1.38)	(0.89)	(111.39)*		(1.41)	(-3.78)*	(15.70)*	(15.70)*	**(-1.90)**	

Note: The above tables constitute the EGARCH (1,1) model selected based in the inclusion of the of CFD investment. T-statistics are in parentheses where $*p<0.01$, $**p<0.05$ and $***p<0.1$.

Table 2.7: *EGARCH (1, 1) results for international exchanges (continued)*

Exchange	b_0	b_1	b_2	b_3	ω	α	δ	β	γ (t-stat)	Log-L
Thailand	0.0476108	0.0294668	0.2369079	0.3411082	0.0942332	-0.0509477	0.294543	0.9220227	**-0.0123245**	-6132.744
(SET)	(1.84)	(1.80)	(18.22)*	(12.07)*	(18.57)*	(-5.41)*	(18.16)*	(199.87)*	**(-1.78)**	
Korea	0.0644508	-0.002693	0.0574305	0.637162	0.0129892	-0.0128527	0.143761	0.9937363	**-0.0098821**	-5852.682
(KOSPI)	(3.13)*	(-0.19)	(6.01)*	(49.71)*	(5.07)*	(-2.11)***	(14.55)*	(619.83)*	**(-2.85)****	
Norway	0.0343918	0.0267813	0.230738	0.5140405	0.0052922	-0.0338077	0.1690835	0.9777189	**+0.0095013**	-4889.706
(BORS)	(2.00)***	(2.06)***	(13.20)*	(24.67)*	(2.31)***	(-3.79)*	(15.13)*	(278.01)*	**(2.48)***	
New Zealand	0.0060928	0.0793763	0.3203228		0.0067965	-0.0357309	0.10835731	0.986933	**-0.002945**	-3179.332
(NZ15)	(0.60)	(5.28)*	(30.76)*		(2.86)**	(-5.19)*	(10.08)*	(435.99)*	**(1.82)**	

Note: The above tables constitute the EGARCH (1,1) model selected based in the inclusion of the of CFD investment. T-statistics are in parentheses where *p<0.01, **p<0.05 and ***p<0.1.

Table 2.8: *EGARCH (1, 1) results for the ASX exchange*

Timeframe	b_0	b_1	b_2	b_3	ω	α	δ	β	γ (t-stat)	Log-L
CFDs Intro	0.0251	-0.07713	0.2073	0.30907	0.1612	-0.0747	0.11351	0.97499	**-0.00783**	-2459.755
Obs:2156	(2.19)***	(-4.61)*	(24.36)*	(19.52)*	(3.42)*	(-6.94)*	(7.66)*	(7.66)*	**(-1.85)**	
CFDs With	0.02258	-0.1082	0.29381	0.3860	0.000481	-0.09498	0.12803	0.96566	**+0.035583**	-2154.262
Obs:2079	(1.68)	(-6.20)*	(27.38)*	(17.22)*	(0.10)	(-7.18)*	(7.18)*	(143.25)*	**(3.97)***	
Total Period	0.02046	-0.07567	0.2425	0.33842	0.008487	-0.07711	0.11819	0.97986	**-0.010955**	-3395.23
Obs:3249	(1.88)	(-5.28)*	(30.25)*	(22.01)*	(2.96)**	(-8.96)*	(8.62)*	(255.54)*	**(-2.71)****	

Note: The above table shows the associated EGARCH(1,1) coefficients in the period before CFD segregation to the ASX CFD exchange. T-statistics are in parentheses where *p<0.01, **p<0.05 and ***p<0.1.

Table 2.9: *Changes in GARCH coefficients under investigation after the introduction of CFDs*

Exchange	Persistence	Autoregressive effect of returns	Asset-specific variance	Efficiency indicator improvements	Efficiency indicator dis-improvements
DJI	-0.0027415	-0.0849611	-0.287839	2	1
S&P500	0.003501	-0.123891	-0.1437854	1	2
FTSE100	-0.0300151	-0.016439	0.08374652	3	0
TSX	-0.0071038	-0.0277667	0.5159199	3	0
BME	0.0180705	-0.0129184	0.2626819	2	1
DAX	0.0163129	0.0426795	0.5254974	0	3
SSE	-0.0501976	-0.0254923	0.0328976	3	0
NIKKEI	0.0165427	0.0251353	0.4742397	0	3
ISEQ	-0.0681647	-0.0700652	0.0762007	3	0
JSE	-0.0142878	-0.1712406	4.4041996	3	0
MIB	0.001738	0.0104627	0.1658664	0	3
KOSPI	-0.0038475	-0.0640878	-0.9113792	2	1
SET	-0.0182689	-0.0130586	0.9876472	3	0
BORS	-0.0211461	-0.0820884	-0.9719398	2	1
NZ15	0.0132494	-0.0270306	0.0703533	3	0

Note: The first efficiency metric investigated is the $\alpha_1 + \beta_1$ coefficient which indicates the persistence of shocks from the pre-CFD to post-CFD introduction periods. A reduction in this persistence indicates the increase in market efficiency. In the 15 exchanges investigated 9 exchanges show a decrease. Investigating the second coefficient β_1, where a decrease indicates a decrease in the autoregressive effect, thus indicating a weak form improvement in market efficiency. Given that the two periods investigated for each exchange signify the introduction of CFDs as tradable products in the market, b_1 becomes an important statistic. This, of course, is only indicative of the time period of the introduction and cannot include other factors that effected market efficiency. The final test is based on the asset-specific variance of the exchanges pre-CFD introduction and post-CFD introduction.

Applying the same statistics to the Australian CFD introduction and subsequent withdrawal with the creation of the ASX exchange offers interesting results as seen in table 2.10. In terms of market efficiency, we can see that the introduction of CFDs was accompanied by an increase in the persistence of shocks, but also saw a decrease in the autoregressive effect and a decrease in variance. This would signify that the introduction of CFDs increased market efficiency. In the period of CFD withdrawal, we can see that there was an increase in the persistence of shocks, an increase in the autoregressive effect and also an increase in the variance. This signifies that there was a decrease in market efficiency in the ASX after the creation of the segregated ASX CFD exchange. Overall, these results indicate that the inclusion of CFDs benefitted exchange dynamics through efficiency improvements, whereas their withdrawal is linked with a period of efficiency deterioration.

Table 2.10: *Changes in GARCH coefficients for the ASX before and after regulatory changes*

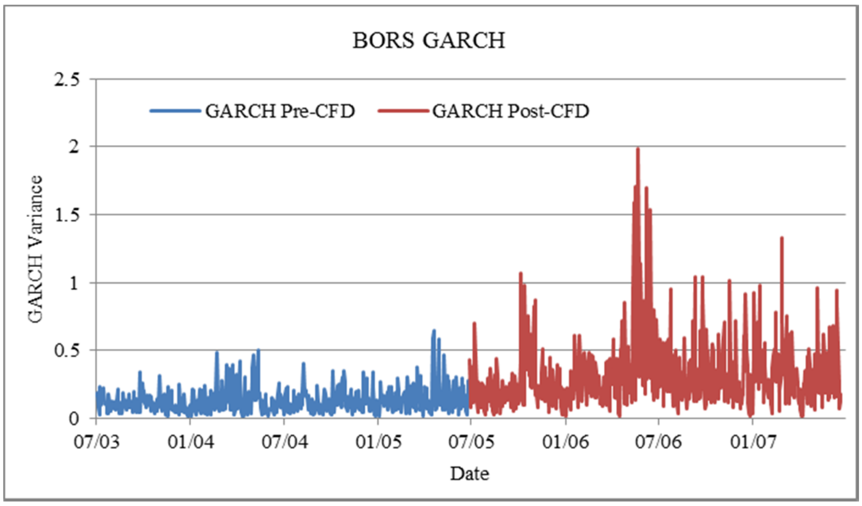
	GARCH Persistence		GARCH Autoregressive Effect		GARCH Asset-specific Variance	
Exchange	**Pre-CFD**	**With-CFD**	**Pre-CFD**	**With-CFD**	**Pre-CFD**	**With-CFD**
ASX	0.946132	0.9867741	0.2210988	-0.1231376	0.4746955	0.3536470
	With-CFD	**Post-CFD**	**With-CFD**	**Post-CFD**	**With-CFD**	**Post-CFD**
ASX	0.9867741	0.974623	-0.1231376	-0.0858967	0.3536470	1.1358219

Note: We have to look at the ASX in two distinct time periods. The first being the introduction of CFDs and the second being the withdrawal. In terms of market efficiency, we can see that the introduction of CFDs was accompanied by an increase in the persistence of shocks, but also saw a decrease in the autoregressive effect and a decrease in variance. This would signify that the introduction of CFDs increased market efficiency. In the second period, we can see that there was an increase in the persistence of shocks, an increase in the autoregressive effect and also an increase in the variance. This signifies that there was a decrease in market efficiency in the ASX after the creation of the segregated ASX CFD exchange.

This higher link between poorly capitalised exchanges and the persistence of shocks indicates that the inflow of CFDs has a larger effect on market efficiency in poorly capitalised exchanges. This may be attributed to the fact that the leverage in CFDs may not have been previously available in some of these exchanges. After investigating the specific changes in the persistence of shocks, the autoregressive effect and the asset-specific variance between the pre-CFD and post-CFD introduction period, further analysis finds that highly capitalised exchanges show more beneficial market efficiency effects than that of poorly capitalised exchanges. After further examination, it is found that this effect can be explained simply through added liquidity effects, when larger exchanges have higher estimated liquidity inflows from CFDs, thus enhancing efficiency. The efficiency benefits stemming from increased market liquidity are associated with the increased speed of the transfer of information throughout the market.

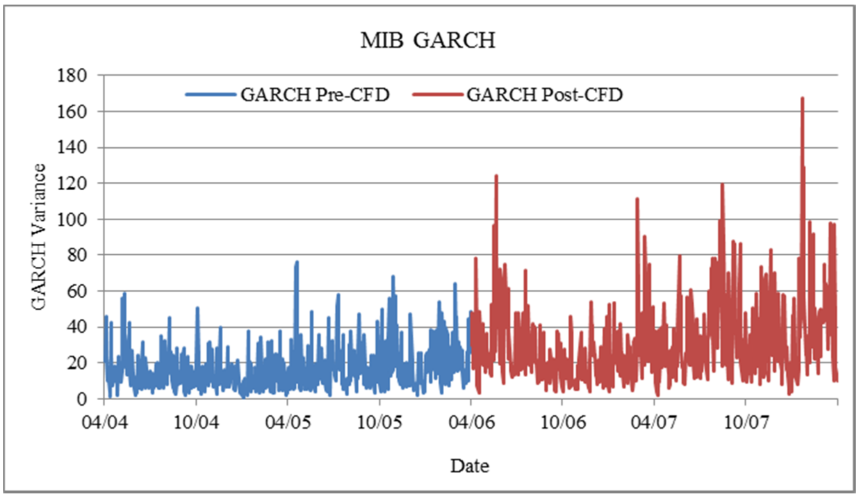
The GARCH analysis was also conducted in a short and long term viewpoint. The sample periods were broken down into two and ten year windows around CFD introduction. Though significantly more sensitive, volatility was uniformly greater in international exchanges in the short-term at the time of CFD introduction. This indicates a larger short-term shock at the point of CFD arrival, with the effect diluted in the following period – generally in the following two years after introduction. The most obvious volatility changes are found in Norway, Italy and Spain and can be found in figures 2.3, 2.4 and 2.5. Other exchanges show similar, yet not as substantial, effects as those seen in these countries.

Figure 2.3: *BORS - Norway GARCH variance*



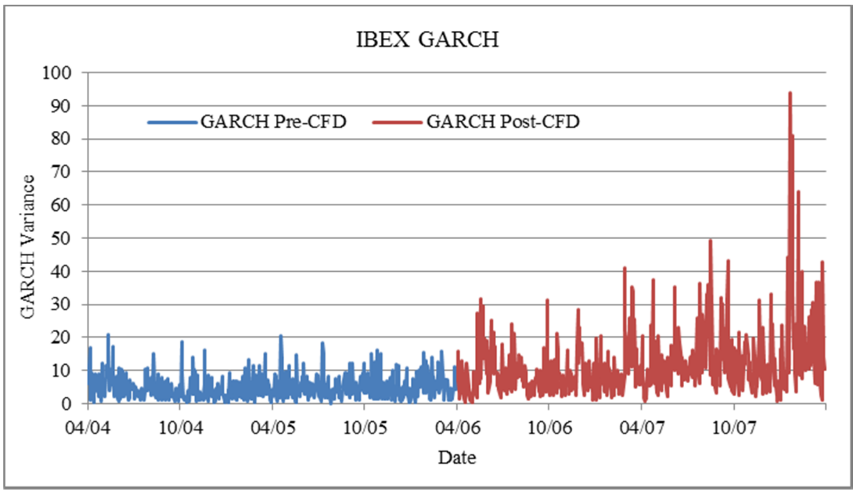
Note: The Oslo BORS in Norway shows a clear increase in variance in the period after the introduction of CFDs. Spikes in variance also appear more pronounced adding further weight to the argument that CFD exposure increased the depth of volatility in low capitalisation exchanges.

Figure 2.4: *MIB - Italy GARCH variance*



Note: The Italian Stock Exchange saw the introduction of derivatives in 2006. We can see a clear increase in variance immediately after their introduction followed by a period of sustained low volatility. This then trends upwards, indicating that CFDs may have in fact had a destabilizing effect.

Figure 2.5: *IBEX - Spain GARCH variance*



Note: The IBEX in Spain shows a clear increase in GARCH variance after the arrival of CFDs. It also appears to be upward trending in the two year period after their introduction in early 2006. The latter section of the graph is associated with the onset of the global recession and international market crash, but the increase in volatility is visible immediately.

2.6. How have CFDs affected volatility?

Quite simply, CFDs have the power to create net benefits to an exchange – due to the added liquidity from the margin that is used to open new positions for CFD investors. One major issue is based on the decision-making process of CFD traders and their investment horizons. If CFDs were to be used as long term investment vehicles, there would have to be additional returns sought due to the commissions and interest charges associated with holding the positions overnight. Thus buy and hold investors would not find this method sustainable. Thus, short term speculative investors are the most likely to use these products. But how can the introduction of CFDs reduce volatility? Simply this can be explained by looking at some level 2 data prior and post to the introduction of CFDs. We will focus on ABCD plc. as an example. If the price of a share in ABCD plc. is €0.12 at 1pm, a trader will be left with a situation such as table 2.11.

Table 2.11: *Level 2 trading data example with no CFD transactions*

ABCD plc. 0.12 (-2.50%) 13.01 Vol: 2,400,575					
Buy Orders	(Volume)	Price to buy	Price to sell	(Volume)	*Sell Orders*
13.01 (1)	**80,000**	**0.115**	**0.125**	**90,000**	**13.01 (3)**
13.01 (3)	50,000	0.110	0.130	30,000	13.01 (5)
13.00 (4)	150,000	0.100	0.140	40,000	13.01 (1)
13.00 (2)	90,000	0.090	0.150	10,000	13.01 (2)
13.00 (4)	250,000	0.080	0.160	5,000	13.01 (4)
13.01 (1)	175,000	0.070	0.170	15,000	13.01 (4)

Note: Table 2.11 represents an example of the level 2 data that a trader would view for ABCD plc. in a situation without CFD hedging through stop-losses and limit orders present in the market. The left and right hand columns represent the time and trader number that implemented the order to buy or sell the stock.

We can see from the example level 2 data in table 2.11, that the current price of ABCD plc. stock is €0.12. If for example, a CFD trader has bought €2 million worth of ABCD at €0.12 using 10% margin, and we assume his net wealth is €5 million (€2 million in CFDs, €3 million cash with the broker), this means that a 25% fall in share price results in a total loss for the CFD trader.The CFD broker inputs a limit-order to sell shares at 1.03pm to protect against the price 'gapping[47]' their required minimum threshold. The scale of this position becomes evident in table 2.12. The €2 million CFD investment at €0.12 is the equivalent size of a €20 million fully margined investment (166,666,667 shares at €0.09). If the price falls to €0.09, the trader has lost his entire available margin, thus to protect the company, the broker will leave an order to sell the shares at €0.09. Other market agents, unaware of what is transpiring in this brokerage will now see the level 2 data[48] change to:

The other traders in the market can now see the extremely large volumes at €0.09 and view this as a large 'sell signal'. But if the same scenario was to occur (ignoring the current shorting ban) and a trader was short at the same levels, the brokerage would have the same order to buy at €0.15. This would effectively trap the market between €0.09 and €0.15. The other non-leveraged traders would simply have to wait until the highly leveraged CFD trader's exit the market before normal fully-margined trading resumed. Thus, the volatility of the exchange would fall as the normal mechanics of daily trading are affected.

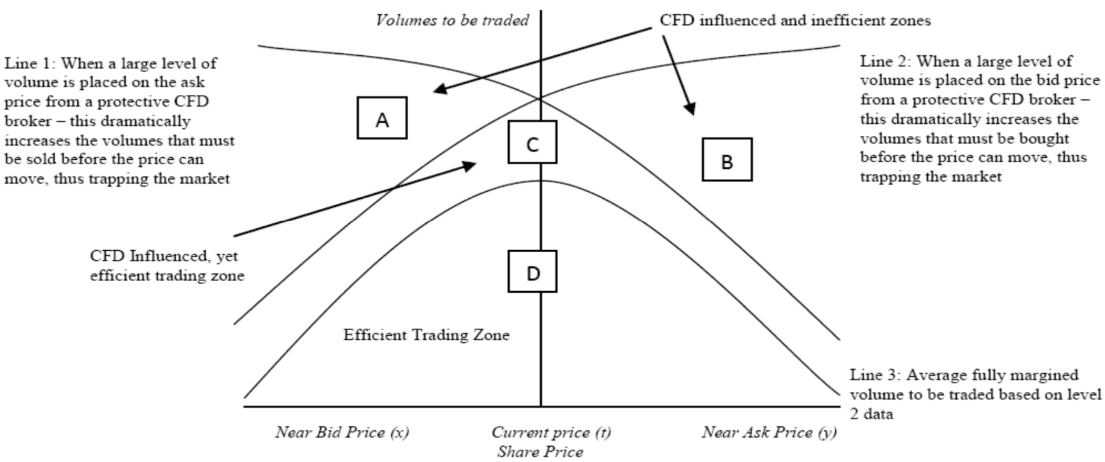
[47] A gap is a break between prices on a chart that occurs when the price of a stock makes a sharp move up or down with no trading occurring in between. Gaps can be created by factors such as regular buying or selling pressure, earnings announcements, changes in an analyst's outlook or any other type of news release.
[48] Level 2 data is also known as the order book for trading a financial product and generally includes information such as: the highest bid prices, the lowest ask prices and the numbers of shares/contracts that are available at each ask and bid price.

Table 2.12: *Level 2 trading data example with CFD broker hedging implemented*

ABCD plc. 0.12 (-2.50%) 13.05 Vol: 2,400,575					
Buy Orders	(Volume)	Price to buy	Price to sell	(Volume)	*Sell Orders*
13.05 (1)	**80,000**	**0.115**	**0.125**	**90,000**	**13.05 (3)**
13.05 (3)	50,000	0.110	0.130	30,000	13.05 (5)
13.00 (4)	150,000	0.100	0.140	40,000	13.01 (1)
13.05 (2)	***166,756,667***	0.090	0.150	10,000	13.01 (2)
13.00 (4)	250,000	0.080	0.160	5,000	13.01 (4)
13.01 (1)	175,000	0.070	0.170	15,000	13.01 (4)

Note: Table 2.12 represents an example of the level 2 data that a trader would view for ABCD plc. after the implementation of a stop-loss order to hedge the CFD broker's counterparty risk of an investor's €2 million investment through CFDs. The order of 166,666,667 shares at €0.09 represents a full hedge against the €2 million position opened at €0.12 (The new value of 166.756,667 shares at €0.09 is the combination of the CFD position of 166,666,667 shares and the existing 90,000 shares present before the CFD order was implemented). This also creates a significant 'overhang' on the bid-side of the market which is clearly evident from the scale of the position in comparison to other traders in the market on both the bid and ask side of the market. The left and right hand columns represent the time and trader number that implemented the order to buy or sell the stock.

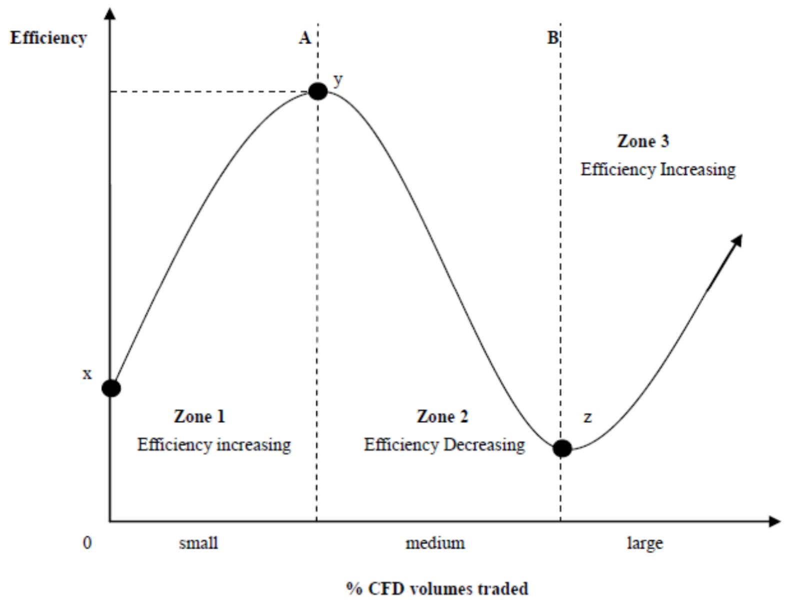
Figure 2.6: *The impact of CFD volumes on the bid and ask price*



Note: Figure 2.6 above shows the theoretical situation when CFD volumes are placed in an exchange to be bought or sold by the market

Therefore, there appears to be a threshold of CFD trading that is beneficial to the market mechanics. If there is a high level, then CFD traders can trade amongst one another and frequently buy and sell. The alternative is a few small CFD traders that are not proportionately much larger than that of the largest fully margined traders. In figure 2.6, we can see that area D is the trading zone with no CFD trading and when investigating the volumes waiting to be traded at the current share price, there is on average higher volumes resting at the bid or ask price closest to that of the last traded price. But, when a CFD broker must hedge the risk of the company from the possibility of losing funds due to the proximity of a loss to a large client, the broker must place an order into the market to buy or sell the shares owned on the CFD trader's behalf. In this situation, the action pushes the volumes sought or demanded closest to the current traded price, with the side of the market dependent on whether it is a buy-side or sell-side action. Therefore, areas A and B in figure 2.6 are zones of inefficiency, or trading zones close to the current trading price that are influenced by CFD trading. Zone C, is the intersection of both the scenarios, and can be explained simply as an appropriate amount of CFD trading on both sides of the market that inevitably matches and promotes efficiency.

Figure 2.7: *CFD trading and associated levels of market efficiency*



Note: Figure 2.7 shows the relationship between the percentage of volumes on exchange that are CFD traded and market efficiency which is measured using persistence, asset-specific variance and the autocorrelation of returns for the equity for which the CFD is offered. At point X, there is not CFD trading available in the market, thus volumes traded are devised of fully margined trader. Point X also represents the initial measure of market efficiency which consists of no-CFD trading. To the left of A, there are a small number of CFD-traders in the market, whose overall market power cannot dominate that of fully margined traders. In fact, in zone 1, these CFD traders add liquidity to the market, thus efficiency increases to X_1.Note that the highest efficiency occurs atX_1, full efficiency cannot be achieved as the market would be operating solely in response to fundamentals. This is close to impossible given the presence of speculators. To the right of line B, CFD traders have a dominant impact on the decreasing number of fully-margined traders. In this situation, though the volumes traded are now larger, the majority CFD traders present in the market with just fully margined traders such as that found in zone 1. Zone 2 is deemed a zone of inefficiency as fully-margined traders are unable to absorb the increasing inundation of leveraged CFD traders. Efficiency falls from y to z as more leveraged traders enter the market.

This scenario also holds true for exchange dynamics, where the liquidity of the exchange appear to be directly associated with the amount of CFD volumes that can be absorbed. There appears to be a threshold where liquidity is high enough to absorb the CFD volumes, or CFD volumes are not high enough to have an effect.

In figure 2.7, there appears to be a trading zone (i.e.: zone 2) between lines A and B, where the fully-margined market is unable to efficiently absorb the amount of CFD volumes entering the market. To the left of line A in zone 1, the percentage of CFD trading is too small to have any effect, thus fully-margined traders dominate, and to the right of line B in zone 3, there is a sufficient number of CFD traders trading with one another to endorse market efficiency, thus the trading practices of these agents cancel one another in a similar manner to the actions of numerous fully margined traders. With the availability of data of the exact percentages of CFD traders per day, it would be possible to calculate these zones and input thresholds of CFD trading to counter-act any efficiency reducing affects these products may have.

Since it is found that CFDs have decreased exchange volatility after their introduction; one must ask how this has occurred. The most obvious explanation is based on the assumption that there are numerous irrational or risk-loving traders whose trading activity tends to increase volatility above the rational-equilibrium level. It must also be assumed that CFDs are their preferred investment product for quickly and cheaply entering and exiting their market of choice. Without CFDs available, the speculative traders submit their orders directly to the market using cash, thus increasing market volatility. But using CFDs, these same traders submit their orders using CFDs with a 10% cash margin and the rest of the order is offset by a broker using a stop-loss order for the remaining order size. This stop-loss protects the broker from potential 'gaps' in the market. This offsetting stop-loss order entered at the same time as the purchase order will lower the volatility increase caused by the purchase order. Its impact is diluted by the presence of the stop-loss. In this way, stop-loss orders can account for the lower volatility attributed to the results with CFDs. Note that if the trader is risk-loving and tends to increase volatility, then a buy-plus 90% stop-loss has less impact on volatility than a buy order of the same magnitude without an offsetting stop-loss.

2.7. Conclusions

Options, futures and other derivatives have become widely accepted investment tools in many international markets in recent decades, and their advantages and disadvantages are known widely and understood. CFDs on the other hand, have become a commonplace investment tool in markets that until their inception had no leveraged exposure available. Have they affected market volatility and efficiency?

In terms of liquidity effects, the EGARCH analysis indicates that the ASX was subjected to a decrease in long-term volatility after the introduction of CFDs and an increase in volatility after the creation of the separate ASX CFD exchange, when CFD investment fell. Also, 32 of the 36 individual equities investigated showed a similar decrease in volatility. A similar EGARCH model based on the international exchanges investigated show that 13 of the 16 exchanges had reduced volatility in the period after the introduction of CFDs.

Using GARCH models and investigating changes in market efficiency, after the introduction of CFDs, poorly capitalised exchanges are associated with a large reduction in the persistence of shocks and lower autoregressive return effects, but larger exchanges appear to benefit more from large reductions in asset-specific variance. Overall, 7 of the 16 exchanges showed a distinct improvement in all three aspects of market efficiency investigated after the inclusion of CFDs as a trading tool, with 11 showing an improvement in at least two of the three. The DAX (Germany), MIB (Italy) and Nikkei (Japan) showed a dis-improvement in market efficiency based on the investigated GARCH measures.

In terms of the dynamics of CFD investment, this paper finds that in the Australian case, equities with larger proportions of CFD investment are subjected to higher price volatility. This is similarly the case for equities with higher trading volume being associated with higher volatility. Alternatively, equities with higher market capitalisation and nominal prices are associated with lower price volatility. Higher priced equities are much more risky to buy as their nominal price moves more than cheaper stock, thus this may point out that lower priced equities are the prime focus of CFD traders seeking quick price moves. This is based on the affordability aspect for those traders with little initial starting capital, thus equity with low nominal values appear to be more attractive. This paper has also found that estimates of CFD volumes in Australia appear in line with many international analysts forecasts, and some equities in fact have more shares traded in CFD format than that of normal fully margined trading.

What do these results mean? CFDs appear to have helped the markets they have been introduced in, but only from a long-term viewpoint. The products appear to have reduced market volatility, while simultaneously offering a new tradable product. This volatility reduction stems from CFD brokers implementing stop-loss and limit-orders in the market to protect themselves from client's losses being transferred to the brokers accounts. This also gives rise to bid and ask price 'overhangs' which theoretically can reduce volatility simply through a reduction in trading liquidity. Unfortunately, CFDs also appear to be associated with more short-term volatility, which may be associated with the increased used of leverage through CFDs. Another feasible explanation for this larger volatility is based on the use of CFDs as a short-term trading tool. Ease of use, large levels of available margin, and large overnight holding interest costs offer evidence supporting the use of CFDs as a high frequency trading tool, a form of trading found to increase market volatility. It appears as if CFDs may in fact be playing a role in accelerating mass deviations from short-term price dynamics.

To gain a role as a commonplace investment technique, CFDs have to become more transparent. This is vital to their long-term success. Sources of market data should be forced to show how many CFDs are traded as a proportion of total volumes traded and also the stop losses and limits in place for those trading. Options and futures have separate exchanges, and can be clearly seen so if there are large volumes of each purchased their effects can be viewed by informed traders. The creation of the ASX CFD exchange for the first time, enabled the public to see trade data based on CFD transactions. It was therefore possible to calculate the proportion of the market that was leveraged using this product. More importantly, it was possible to view CFD-specific stop-losses and limit-orders. These market orders are theoretically capable of creating market 'overhangs', thus directly influencing market efficiency.For CFDs to continue their existence in a transparent and fair market, market makers must be forced to invest in the technology transparency a priority.

Chapter 3: Have Exchange Traded Funds influenced commodity market volatility?

Abstract: *Exchange Traded Funds (ETFs) have existed since the late 1980s but were first traded on commodity markets in the early 2000s. Their inception has been linked by some market analysts with the large growth in commodity market price increases and volatility evident between 2007 and 2009. This chapter investigates the role that ETFs have played, either as an accelerant for mispricing in international commodity markets, or alternatively as a mechanism to increase efficiency through added liquidity. In a secondary analysis, this chapter investigates whether the stylised characteristics of ETFs are more or less pronounced in larger sized commodity markets than in small markets. The results indicate that larger ETF investments are associated with higher EGARCH volatility. Smaller commodity markets are found to have increased efficiency after the introduction of ETFs indicating that there are some benefits from new ETF investment in markets below $4-$5 billion size, but the associated caveat is that of increased volatility indicating potential pitfalls in the ETF rebalancing process. It appears that ETFs have made commodity markets more efficient through a new influx of trading counterparties, but they appear to be associated with a cost. The need for regulation of investment size and market ownership limits therefore cannot be rejected.*

3.1. Introduction

This chapter investigates whether Exchange Traded Funds (ETFs) have had a role in the amplification of volatility in international commodity prices or alternatively whether their introduction has benefited the same markets through increased liquidity. In this chapter we segregate commodity markets by size to investigate whether ETF investment affected markets differently. We examine whether smaller commodity markets have been able to cope with the increased flow of funds.

ETFs are usually registered investment funds that track a particular index, but can be traded with the same properties as equities. The ETF itself is a bundle comprising the individual components of the chosen index or sought investment strategy (for example, based on price or sought level of risk). For example, a financial ETF could potentially be comprised of a fund which has invested in the main financial services stocks of a particular exchange. The investment strategy of the ETF is decided by the provider and can be based, for example, on the market capitalisation or share price of the individual elements of the ETF. ETF investors have benefited from tax-efficiency in comparison with mutual funds as they simply track many of the indexes they invest in. This lends to a reduction in operating and transaction costs due to the passively-managed styles of ETFs. ETFs have evolved in recent years becoming more complex. It is now possible to buy shares of an ETF investing in the underlying index using additional leverage, choice of investment stances (long or short) or based on different trading strategies. Many market analysts view ETFs as a tool offering an opportunity for smaller investors to enter markets they otherwise could not. In some markets, the costs of direct entry are simply too high for the smaller investors. But the creators of ETFs are able to pool the investments of numerous investors. The ETF divides the product they have invested in into shares and sells them in a secondary market.

It has been found that ETF investor trading habits are associated with more frequent trading, which has been found to reduce overall market returns (Jares & Lavin 2007, Gastineau 2008). John Bogle, the founder of the Vanguard Group[49], has argued that ETFs are the source of short-term speculative strategies. Though offering the view that an ETF held for a prolonged period of time can be a good investment, the trading commissions significantly reduce the returns to the investor and that in some cases the investor is not receiving the diversification that is initially offered by the ETF provider. Some analysts argue that ETFs are capable of manipulating market prices, and particularly that of short ETFs[50] (Jing 2006). In some cases, it has been argued that the index that has been offered as an ETF may be misrepresented. Though it may be based on a particular sector of the economy or market, it is at the discretion of the ETF creator to determine which individual components are in the fund. Higher market volatility is also associated with a tracking error[51] between the returns of the ETF and the returns of the market. In most cases, ETFs have a low tracking error. But in markets with a substantial reduction in market liquidity, there are significant problems with traders completing their orders at the required price, thus they have to pay more for a significant proportion of their sought investment product (Robinson et al 2010, Kosev & Williams 2011). The effects of contango[52] and backwardation[53] are substantial, particularly when an ETF is being created based on constituents formed from commodity futures.

The main benefits of ETF investment is the ease of diversification, low expense ratios and tax efficiency. This comes with all the standard structure of a normal equity with options[54], short

[49] The Vanguard Group is an American investment management company that manages approximately $1.4 trillion in assets, based in Malvern, Pennsylvania. It offers mutual funds and other financial products and services to individual and institutional investors in the United States and abroad.

[50] A short ETF, or also known as an inverse ETF is constructed by using various derivatives for the purpose of profiting from a decline in the value of an underlying benchmark. Investing in these ETFs is similar to holding various short positions, or using a combination of advanced investment strategies to profit from falling prices.

[51] Tracking error is a measure of how closely a portfolio follows the index to which it is benchmarked.

[52] Contango refers to the market condition wherein the price of a forward or futures contract is trading above the expected spot price at contract maturity. The resulting futures or forward curve would typically be upward sloping (i.e. "normal"), since contracts for further dates would typically trade at even higher prices.

[53] Backwardation refers to the market condition wherein the price of a forward or futures contract is trading below the present spot price. The resulting futures or forward curve would typically be downward sloping (i.e. "inverted"), since contracts for farther dates would typically trade at even lower prices.

[54] An option is a derivative financial instrument that establishes a contract between two parties concerning the buying or selling of an asset at a reference price during a specified time frame. The buyer of the option gains the right, but not the obligation, to engage in some specific transaction on the asset, while the seller incurs the obligation to fulfill the transaction if so requested by the buyer.

selling, stop losses and limit orders available. ETFs generally have lower costs because most are passively managed, thus ETF managers do not regularly buy and sell the individual elements of the ETF, but rather hold the components for long term return. ETFs can be bought and sold at any time during the trading day in comparison to mutual funds that can only be sold at the end of each trading day when their net asset value (NAV) is calculated. One of the major volatility linked issues associated with ETFs is the rebalancing trades that occur at the end of the day. For ETFs to meet their investment mandates, it is necessary for them to rebalance their trading as market movements require. Many analysts have thought that this rebalancing process that is can cause excess volatility (Rompotis 2009, Humphries 2010). Many market experts believe that ETF rebalancing due to the unwillingness and reticence to hold positions overnight is boosting late-day volume, with some estimates in the range of 20% to 30% of last hour trading being accredited to ETFs (Avellaneda & Zhang 2009, Knain-Little 2010). In 2010, Morgan Stanley estimated that ETFs account for about 30% of daily listed market volume, which is three times more than in 2005. The Investment Company Institute in 2010 believed that more than $780 billion is invested in ETFs (Milonas & Rompotis 2006). Leveraged ETFs have drawn their own concerns due to the amplified volumes purchased and sold associated with fund rebalancing. If one was to investigate broad funds like index trackers, the rebalancing process of one large ETF investment could be as large as a new position to buy or sell on every selected stock on the ETF index in question. Another effect associated with increased ETF trading is a rise in market correlations. A ‘herd effect’ has been seen by analysts as ETF trading mirrors falls in individual shares (Miffre 2007). This has been amplified by current global uncertainties, as investors are now less willing to hold overnight positions due to the increased risk of off-market-hours price fluctuations. This phenomenon is clearly more pronounced since early 2008, signalling the change in risk preferences of investors as markets started to fall precipitously in late 2008.

From 1986 to 2004, the return correlation between soybeans and oil was almost zero. Since ETFs were established and have become a popular trading product, this correlation has increased to 0.6. Similarly, from near zero correlation in the previous period of investigation, the arrival of ETFs has been linked to correlation increases between oil and cotton (0.5), oil and live cattle (0.4) and oil and copper (0.6) which have all increased dramatically from close to zero. Xiong and Tang (2011) believed that ETFs are associated with this increase in correlations because the same findings are not found in Chinese commodity markets, which are not available to foreign investment, so that ETFs cannot enter these markets to purchase the underlying commodity components to create their funds.

The Financial Services Authority[55] (FSA) in the United Kingdom, have also voiced strong concerns about the role of ETFs when investigating high volatility[56]. They claim that the

[55] The Financial Services Authority (FSA) is a quasi-judicial body responsible for the regulation of the financial services industry in the United Kingdom. Its board is appointed by the Treasury and the organisation is structured as a company limited by guarantee and owned by the UK government. Its main office is based in Canary Wharf, London, with another office in Edinburgh. When acting as the competent authority for listing of shares on a stock exchange, it is referred to as the UK Listing Authority (UKLA), and maintains the Official list. The FSA's Chairman and CEO is Lord Turner of Ecchinswell and Hector Sants. On 16 June 2010, the Chancellor of the Exchequer, George Osborne, announced plans to abolish the FSA and separate its responsibilities between a number of new agencies and the Bank of England.

[56] Retail Conduct Risk Outlook – Financial Services Authority (FSA), United Kingdom, February 2011.

rapid growth of the ETF markets has led to a high level of innovation in this product area. They believe that this created the risk that consumers do not understand the difference between product types in terms of investment strategy, tax status and risk. The FSA found that ETFs have changed in complexity, thus causing a lag in terms of information and education for investors. The lack of familiarity of the market with ETFs has the potential to exacerbate the product's risk. Counterparty and collateral risk are also important risks associated with ETFs. Also, conflicts of interest are found to arise based on the structure of the products. The laws governing ETFs are generally based in the country that domicile the product, rather than that of the country in which the product is being offered. The FSA voiced strong concerns about this point, along with concerns that the marketing and promotional material for complex ETFs directed at retail investors may not always adequately reflect all the various risks inherent in the products[57]. CFTC Chairman Gary Gensler said in an August, 2009 news release that "position limits should be consistently applied and vigorously enforced" and that "position limits promote market integrity by guarding against concentrated positions." This would have a negative impact on ETFs as investors would be less attracted to opening these positions if limits were imposed. ETF providers are of course opposed to any regulation limiting their products, but some markets that ETFs invest in are simply too small to efficiently absorb the large inflow of investor's funds.

This chapter tests the effects that ETF introduction has had on commodity markets through the use of GARCH and EGARCH techniques. This analysis will help to test whether commodity ETFs have had a detrimental effect on commodity market volatility and efficiency as proposed by market analysts and commentators. This chapter is organised as follows. Section 3.2 describes the relevant previous literature associated with this chapter. Section 3.3 describes the data, methodology and structure of the models used in the analysis. Section 3.4 describes the results while section 3.5 concludes.

3.2. Previous literature

The literature on the volatility effects of ETF introduction in commodity markets remains sparse, though other facets of ETF design have been researched. One of the largest concerns associated with ETFs has been linked with their management, or the investment strategies they apply when constructing the underlying index. Two methods are generally used; the first based on active management, the second on passive management. Active management is based on the investment mandate of the fund and requires rebalancing of the underlying assets based on changes in the particular facets of the index. The rebalancing process may also have to be completed based on changing investment strategies of those investing in the ETF. Passive management involves creation of the ETF, but minimal rebalancing, as it is the reduction in transaction costs that help generate more profits for the ETF manager. Actively managed ETFs have been specifically identified as a responsible component for large spikes in market activity based on rebalancing activities.

[57] 'The HSA is concerned about ETFs', The Financial Times, 28th of February 2011, Izabeela Kaminska

Rompotis (2009) investigated the dynamic effects from these differing styles to find that active ETFs underperform the corresponding passive ETFs and the market indexes. The results find that the percentage correlation between the trading price of the ETF and the underlying indices range between 0.2% and 39.1%. This sentiment is echoed by Gastineau (2004) and Lu and Wang (2009). Trainor (2010) investigated the link specifically between leveraged ETFs and equity market volatility. The author found that there were more than 150 leveraged and inverse ETFs with assets of more than $30 billion in 2010. Intra-day volatility since 2000 was not found to be associated with the rebalancing process of ETF fund managers. This result was also found to hold during the extreme periods of intra-day volatility during the recent subprime crisis. Cheng and Madhavan (2009) find that leveraged ETFs may have a large effect on market-on-close volumes (MOC). Large moves in prices could be further exacerbated by the rebalancing that leveraged ETFs undertake towards the end of the day. Cherry (2004) found that ETFs are on average 17% more volatile than their underlying components and 70% of this volatility can be explained by transaction and holding costs. Madura and Richie (2004) similarly found substantial overreaction of ETFs during normal trading hours and after hours, presenting opportunities for feedback traders.

In terms of underlying pricing reactions, Cheng and Cheng (2002) found significant premiums between three of the major Hong Kong ETFs and their underlying components. Hughen (2003) investigating the arbitrage mechanism on premiums and discounts showed how critical the arbitrage mechanism is in itself towards the pricing of ETFs. Kalaycioglu (2006) investigated the flow-return relationship in ETFs and fails to reject the hypothesis of no-price-pressure on market returns originating from ETF flows. Engle et al. (2002) found that the pricing of ETFs is highly efficient for domestic products but less so for international funds since they face more complex financial transactions and risks. Harper et al. (2006) found that between 1996 and 2001, their investigated ETFs showed higher mean returns and Sharpe ratios[58] than foreign closed-end funds. Madura and Ngo (2008) found that in response to the inception of ETFs there are positive and significant valuation effects on the dominant component stocks of the ETF investigated. Deshpande et al. (2009) when investigating the link between leveraged ETFs and volatility found that the likely impact is still very small based on volume analysis. A Credit Suisse report (2009) found that leveraged ETFs account for 2% of end-of-day trading and is therefore unlikely to have any significant effects. Similarly, a report by Direxion (2009) found that leveraged ETFs do not exacerbate market volatility or compound directional moves from 3.00pm to market close.

Though there is limited research on volatility effects stemming from ETF introduction, derivative introduction and associated volatility offers significant supporting evidence. There are two main branches of thought on the volatility effects of the introduction of derivatives. The first group are those who believe that derivatives trading increases volatility view these derivative products as a market for speculators. The main concern of proponents of this view

[58] The Sharpe ratio tells us whether a portfolio's asset returns are due to smart investment decisions or as a result of excess risk. This measurement is very useful because although one portfolio or fund can reap higher returns than its peers, it is only a good investment if those higher returns do not come with too much additional risk. The greater a portfolio's Sharpe ratio, the better its risk adjusted performance has been. A negative Sharpe ratio indicates that risk-less asset would perform better than the security being analyzed.

is the low margin requirements available that makes the market high risk, as most agents maximise their available funds. This argument originates from the style of investment and mentality of derivatives traders. They use the products to increase their exposure to an asset, thus amplifying their risk. Some authors believe that destabilising effects are evident in the market as this speculative trading originates from uninformed investors (Chatrath et al., 1995). Stein (1987) claimed that futures markets attracted uninformed traders because of their high degree of leverage, which can reduce the information content of prices and can cause destabilising market volatility. This is foundational to the central hypothesis of this paper.

Other papers that support the view that derivative introduction increased spot market volatility include Jeanneau and Micu (2003), Gulen and Mayhew (2000) investigating the United States and Japan, Antoniou and Holmes (2003), Bessembinder and Seguin (1992) and Lee and Ohk (1992). Pok and Poshakwale (2004) and Ryoo and Smith (2004) found similar volatility increases, but also noted greater sensitivity of spot market prices to new information and efficiency improvements through faster information transfers.

Others argue that the introduction of derivatives reduces spot market volatility and in fact stabilises the market. Derivatives are in fact viewed as an efficient medium of price discovery. Other noted benefits include improved market depth, a reduction in market asymmetries and less cash market volatility as found by Kumar et al. (1995) and Antoniou et al. (1998). Other papers that found volatility reductions after the inclusion of their investigated derivative products include Drimbetas et al (2007), Bologna and Cavallo (2002), Nath (2003), and Pilar and Rafael (2002).

The majority of the research based on the link between derivative introduction and volatility change find no significant correlations. Research finding no significant changes includes Shenbagaraman (2003) who also found changes in the nature of volatility, Mayhew (2000), Darrat and Rahman (1995) and Antoniou and Holmes (1992).

Other research based on the introduction of new derivatives looks at changes in market structure, efficiency and market regulation. Powers (1970) and Danthine (1978) show that futures markets improve overall market depth and the availability of information. Schwartz and Laatsche (1991) and Stoll and Whaley (1988) also found evidence of structural improvements in markets after the introduction of futures. Watt, Yadav and Draper (1992) found no change in volatility post-futures, but did find evidence of efficiency benefits. Santoni (1987), Becketti and Roberts (1990) and Darrat, Rahman and Zhong (2002) all find no volatility changes in the period post-derivatives. They argue that from a regulatory perspective that any action to counter non-existent changes would be unwarranted.

3.3. Data, methodology and structure of the models

The primary research question is 'have ETFs had a direct effect on the volatility of the commodity markets in which they have invested?' This research question is investigated through the use of GARCH and EGARCH models testing dynamic changes in the structure of volatility in the pre and post-ETF introduction periods. In table 3.1, we can see the scale of the market for international ETFs for all types of investment product. The United States, United Kingdom, Germany, France, Canada and Japan are among the largest jurisdictions where ETFs are based in terms of domestic assets under management (AUM in United States dollars) as of December 2010. The commodity markets under investigation in chapter 3 are listed in table 3.2. The main international commodity ETFs are included in the investigation, totalling 44 ETFs across 17 commodity markets listed in table 3.3.

The daily return is calculated as $R_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)$. The dataset[59] is based on the daily returns of commodity prices. The estimated dummy variable equals one on and after as the date on which the ETF started issuing as an investment product. To test the robustness of the conclusion of this paper in a similar manner to Pilar and Rafael (2002), two models of the ARCH family will be used, the GARCH(1,1) model and the EGARCH (1,1). The models include a dummy variable to signal inception of the commodity ETF, denoted as zero prior, and one thereafter.

The model also includes the Dow Jones Industrial Average as a proxy for stock market performance. Also, commodity markets are substantially affected by developments from government interest rate decisions and exchange rate movements. The model includes a dollar-weighted basket comprised of the US dollar against numerous international exchange rates. This will serve as a proxy for exchange rate movements. It is theoretically plausible that any drastic interest rate movements that could affect commodity prices would have a similar effect on equity and foreign exchange values. This analysis as a whole will investigate whether ETF establishment had a statistically significant effect on volatility.

[59]All other data in this research is provided by Thompson Reuters Datastream, Bloomberg and finance.yahoo.com and the main econometric software programme used is Stata 11.0.

Table 3.1: *ETF estimated assets under management (AUM$) as of December 2010*

Country	AUM Billion$	Country	AUM Billion$
Australia	1.21	Malaysia	0.19
Austria	0.08	Mexico	5.33
Belgium	0.07	Netherlands	0.3
Brazil	2.23	New Zealand	0.39
Canada	18.36	Norway	0.27
China	2.86	Singapore	1.35
Finland	0.18	Slovenia	0.01
France	47.28	South Africa	1.95
Germany	65.64	South Korea	3.7
Greece	0.18	Spain	5.45
Hong Kong	15.56	Sweden	2.13
Hungary	0.03	Switzerland	9.25
Iceland	0.07	Taiwan	1.51
India	1.86	Thailand	0.1
Indonesia	0.01	Turkey	0.18
Ireland	0.04	United Kingdom	27.68
Italy	1.05	United States	539.06
Japan	30.42		

Note: The above table represents the estimated assets under management (AUM) in billions of US Dollars ($) as of December 2010 for all styles of ETF investment (bond, equity, currency, commodity etc.).

Table 3.2: *Commodity markets under investigation after ETF introduction*

Sector	Commodity	Ticker Symbol	Main Exchange	Contract Size
Energy	West Texas Intermediate Crude Oil	CL / WTI	NYMEX / ICE	1000 barrels
	Brent Crude	B	ICE	1000 barrels
	Natural Gas	NG	NYMEX	10,000 mmBTU
	RBOB Gasoline	RB	NYMEX	1000 barrels
Precious Metals	Gold	GC	CBOT	troy ounce
	Platinum	PL	NYMEX	troy ounce
	Palladium	PA	NYMEX	troy ounce
	Silver	SI	CBOT	troy ounce
Industrial Metals	Copper	HG	LME	Metric Tonne
	Zinc	Z	LME	Metric Tonne
	Aluminium	AL	LME	Metric Tonne
Livestock	Lean Hogs	LH	CME	20 tonnes
	Live Cattle	LC	CME	20 tonnes
	Feeder Cattle	FC	CME	25 tonnes
Agricultural	Corn	C / EMA	CBOT / EURONEXT	5,000 bushels
	Oats	O	CBOT	5,000 bushels
	Soybeans	S	CBOT	5,000 bushels
	Wheat	W	CBOT	5,000 bushels
	Cocoa	CC	NYBOT	10 tonnes
	Coffee	KC	NYBOT	37,500lb
	Cotton	CT	NYBOT	50,000lb
	Sugar (No.11 / No.14)	SB / SE	NYBOT	112,000lb

Note: The above table contains the spot and future commodity markets under investigation in this chapter for effects after the introduction of Exchange Traded Funds (ETFs).

Table 3.3: *Commodity ETFs under investigation and their associated components*

Name	Inception Date	Ticker	Net Asset Value (NAV-$)[60]	Assets under Control (Approximate)
SPDR Gold Trust	18/11/2004	GLD	53,639,130,580	100% Spot Gold (Long)
iShares Silver Trust	28/4/2006	SLV	6,391,704,000	100% Spot Silver (Long)
iShares COMEX Gold Trust	28/1/2005	IAU	4,060,120,500	100% Spot Gold (Long)
United States Oil Fund	10/4/2006	USO	1,798,284,000	100% Long West Texas Intermediate Oil (WTI)
ETFS Physical Swiss Gold Shares	9/9/2009	SGOL	942,835,480	100% Spot Gold (Long)
ETFS Physical Platinum Shares	8/1/2010	PPLT	482,764,500	100% Spot Platinum (Long)
ETFS Physical Palladium Shares	8/1/2010	PALL	392,303,310	100% Spot Palladium (Long)
ETFS Silver Trust	24/7/2009	SIVR	212,539,440	100% Spot Silver (Long)
Proshares Ultra Gold	3/12/2008	UGL	201,204,816	100% Spot Gold (Long - Leveraged x2)
Proshares Ultra Silver	3/12/2008	AGQ	185,041,079	100% Spot Silver (Long – Leveraged x2)
Proshares Ultra-short Gold	3/12/2008	GLL	75,581,303	100% Spot Gold (Short – Leveraged x2)
Proshares Ultra-short Silver)	3/12/2008	ZSL	68,330,286	100% Spot Silver (Short – Leveraged x2)
United States Oil Fund	24/9/2009	DNO	19,344,000	100% Short West Texas Intermediate Oil (WTI)
Powershares DB Base Metal Fund	5/1/2007	DBB	361,890,019	35% Copper Futures, 35% Aluminium Futures, 30% Zinc Futures (Long)
RICI Agriculture ETN	18/10/2007	RJA	340,066,000	20% Wheat, 13.5% Corn, 11.5% Cotton, 8.5% Soybeans, 6% Live Cattle, 6% Sugar, 6% Coffee, 6% Soybean Oil, 3% Lumber, 3% Lean Hogs (All Long Futures)
Powershares DB Precious Metals Fund	5/1/2007	DBP	307,793,517	80% Gold, 20% Silver (Long Futures)
Powershares DB Gold Fund	5/1/2007	DGL	245,001,538	100% Gold Futures (Long)
Powershares DB Energy Fund	5/1/2007	DBE	237,865,865	23% Gasoline RBOB, 22.5% Heating Oil, 22.5% Brent Crude Oil, 22% West Texas Intermediate, 10% Natural Gas (Long Futures)
United States 12 Month Oil Fund	6/12/2007	USL	149,560,000	100% West Texas Intermediate Oil (Long Futures)
iPath Dow Jones – UBS Grain ETN	23/10/2007	JJG	147,658,868	45% Soybeans, 30% Wheat, 25% Corn (Long Futures)
iPath Dow Jones – UBS Natural Gas ETN	23/10/2007	GAZ	126,964,200	100% Natural Gas (Long)
iPath Dow Jones – UBS Copper ETN	23/10/2007	JJC	97,577,845	100% Copper (Long)
Powershares DB Commodity Index Tracking Fund	3/2/2006	DBC	4,312,530,024	12.5% WTI, 12.5% Brent Crude, 12.5% Heating Oil, 12.5% RBOB, 5.5% Natural Gas, 8% Gold, 2% Silver, 4% Aluminium, 4% Zinc, 4% Copper, 5.5% Corn, 5.5% Wheat, 5.5% Soybeans, 5.5% Sugar.

[60] Data correct as of September 2010

Table 3.3: *Commodity ETFs under investigation and their associated components (continued)*

Name	Inception Date	Ticker	Net Asset Value (NAV-$)[61]	Assets under Control (Approximate)
iPath Dow Jones – UBS Commodity ETN	6/6/2006	DJP	2,194,570,508	20% Industrial Metals, 25% Energy, 13% Precious Metals, 6% Livestock, 30% Agriculture
Powershares DB Agriculture Fund	5/1/2007	DBA	2,078,780,343	14% Live Cattle, 13% Coffee, 13% Soybeans, 12% Corn, 12% Wheat, 11% Cocoa, 10% Lean Hogs, 10% Sugar, 5% Feeder Cattle, 3% Cotton (Long Futures)
iShares GSCI Commodity Index	21/7/2006	GSC	1,539,150,495	71% Energy, 13% Agriculture, 7% Industrial Metals, 4.5% Livestock, 3.5% Precious Metals
iPath S&P GSCI Crude Oil Index ETN	15/8/2006	OIL	593,813,780	100% Futures West Texas Intermediate (Long)
Powershares DB Oil Fund	5/1/2007	DBO	557,996,691	100% Futures West Texas Intermediate (Long)
Powershares DB Gold Double Long ETN	28/2/2008	DGP	479,251,500	100% Gold Futures (Long)
Proshares Ultra DJ-UBS Crude Oil	25/1//2008	UCO	421,349,629	100% Futures West Texas Intermediate (Long)
E-TRACS UBS Bloomberg CMCI Gold ETN	1/4/2008	UCI	90,290,054	100% Gold Futures (Long)
Powershares DB Silver Fund	5/1/2007	DBS	80,698,934	100% Silver Futures (Long)
iPath Dow Jones – UBS Platinum ETN	25/6/2008	PGM	79,691,654	100% Platinum Futures (Long)
United States Natural Gas Fund	18/4/2007	UNG	2,432,673,000	100% Natural Gas (Long Futures)
Powershares DB Gold Double Short ETN	28/2/2008	DZZ	75,696,000	100% Gold Futures (Short)
iPath Dow Jones – UBS Sugar ETN	25/6/2008	SGG	74,757,977	100% Sugar Futures (Long)
iPath Dow Jones – UBS Livestock ETN	24/10/2007	COW	72,962,716	69% Live Cattle, 31% Lean Hogs (Long Futures)
Powershares DB Crude Oil Double Short	17/6/2008	DTO	65,424,500	100% Crude Oil Futures (Short – Leveraged x2)
E-TRACS UBS Bloomberg CMCITR Long Platinum ETN	9/5/2008	PTM	65,557,449	100% Platinum Futures (Long)
Powershares DB Base Metal Double Long ETN	18/6/2008	BDD	24,890,000	33% Aluminium, 33% Zinc, 34% Copper (Grade A)
iPath Dow Jones – UBS Coffee ETN	25/6/2008	JO	22,860,000	100% Coffee Futures (Long)
Proshares Ultra-Short DJ-UBS Crude Oil	25/11/2008	SCO	45,170,707	100% West Texas Intermediate Oil (Short – leveraged x2)
United States 12 Month Natural Gas Fund	18/11/2009	UNL	42,000,000	100% Natural Gas Futures (Long)
Powershares DB Gold Short ETN	29/2/2008	DGZ	334,130,000	100% Gold Futures (Short)

[61] Data correct as of September 2010

The GARCH model was developed by Bollerslev (1986) from the ARCH[62] model previously introduced by Engle (1982). The GARCH (p,q) model suggested by Bollerslev is represented as:

$$R_t = bx_t + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t),$$

$$h_t = x_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j},$$

where ε_t is asset specific returns and x_t are other explanatory variables included in the GARCH equation. If q=0, the process reduces to an ARCH(p) process and for p=q=0, ε_t is just white noise. The GARCH(1,1) framework has been extensively found to be the most parsimonious representation of asset-specific variance that best fits and therefore is most adequate to use with many financial time series (Bollerslev, 1987).

The GARCH model used in this paper to investigate spot commodity market volatility changes after ETF introduction is denoted as:

$$R_t = b_0 + b_1 R_{t-1} + b_2 R_{DJIA_t} + b_3 R_{USD_t} + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \text{ and } \alpha_i, \beta_j \geq 0,$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma D_{ETF_t},$$

where $\gamma \geq 0$ in addition to the other non-negativity restrictions above. Thus the value of the variance scaling parameter, h_t, now depends on past values of the shocks, which are captured in the lagged squared residual terms and on past values of itself, which are captured in the lagged h_{t-1} term. h_t is known at the beginning of time t. Ω_{t-1} is the information set at the end of time period t-1. R_{DJIA_t} represents the daily return on the Dow Jones Industrial Average (DJIA) and R_{USD_t} represents the daily return on the main benchmark Federal Reserve dollar-weighted basket. These variables are included in the mean equation to mitigate the GARCH model against United States equity and currency volatility respectively. D_{ETF_t} is included in the variance equation as a representation of the dummy variable included in the GARCH model denoting the arrival of ETFs. This variable takes a value of zero prior to the arrival of ETFs and one thereafter. With GARCH the conditional variance is modelled as a linear function of the lagged conditional variance in addition to the past squared errors contained in the ARCH representation. To offer more parsimonious results, the EGARCH model is used in conjunction with the GARCH analysis.

[62] AutoRegressive Conditional Heteroskedasticity (ARCH) models are used to characterize and model observed time series. They are used whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size, or variance. In particular ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the previous innovations.

The Exponential GARCH model (EGARCH) was first developed by Nelson (1991). The ARCH(p) and GARCH (p,q) models impose symmetry on the conditional variance structure which may not be appropriate for modelling and forecasting stock return volatility. EGARCH models capture the most important stylised features of equity return volatility, namely time-series clustering, negative correlations with returns, log-normality and with other certain specifications, long memory. Nelson (1991) proposed the exponential GARCH or EGARCH model as a method of dealing with the problem.

Under the EGARCH(1,1) framework, the conditional log variance is calculated as:

$$R_t = bx_t + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t),$$

$$\log(h_t) = \omega + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + \beta \log(h_{t-1}) + \delta \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}},$$

The parameters ω, α, β and δ are constant. The EGARCH model has two advantages over the GARCH model. First, the logarithm construction of the conditional variance equation ensures that the estimated conditional variance is strictly positive, thus the non-negativity constraints used in the estimation of the ARCH and GARCH models are not necessary. Also, the parameter δ typically enters the conditional variance equation with a negative sign, thus bad news, $\varepsilon_t < 0$ generates more volatility than good news. In the EGARCH model used, the dependent and independent variables remain similar to those used in the GARCH analysis:

$$R_t = b_0 + b_1 R_{t-1} + b_2 R_{USD_t} + b_3 R_{DJIA_t} + \varepsilon_t,$$

$$\text{where } \varepsilon_t | \Omega_{t-1} \sim N(0, h_t).$$

But the specification of the conditional variance equation now becomes:

$$\log(h_t) = \omega + \alpha \left[\left| \frac{\varepsilon_{t-j}}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right| \right] + \beta \log(h_{t-1}) + \delta \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma D_{ETF_t},$$

h_t is known at the beginning of time t. Ω_{t-1} is the information set at the end of time period t-1 which makes the leverage effect exponential instead of quadratic and therefore, estimates of the conditional variance are guaranteed to be non-negative. The EGARCH model allows for the testing of asymmetries, which are picked up in the β term. Similarly to the GARCH methodology, R_{DJIA_t} represents the daily return on the Dow Jones Industrial Average (DJIA) and R_{USD_t} represents the daily return on the main benchmark Federal Reserve dollar-weighted basket. These variables are included in the mean equation to mitigate the EGARCH model against United States equity and currency volatility respectively. D_{ETF_t} is included in the variance equation as a representation of the dummy variable included in the EGARCH model denoting the arrival of ETFs. This variable takes a value of zero prior to the arrival of ETFs and one thereafter. When $\beta = 0$, the model is symmetric, but when β <0, then positive shocks generate less volatility than negative shocks. The model captures the asymmetric features of the dataset, which occur when an unexpected drop in price due to bad news increases volatility more than an unexpected increase in price of a similar magnitude because of good news. The model expresses the conditional variance of the variables as a non-linear function of its own past standard innovations. This is similar to the methodology used and explained in chapter two.

3.4. Results

3.4.1. EGARCH investigation of the period of ETF introduction

This section conducts an EGARCH investigation of the period before and after the introduction of ETFs. The inclusion of a dummy variable in the volatility equation, equal to zero in the period before ETFs and one thereafter, provides a coefficient denoted as gamma (measuring the volatility change) between the periods before and after ETF introduction. External sources of volatility stemming from currency and equity markets are controlled by these variables' inclusion in the mean equation of the EGARCH model; providing results as closely associated to commodity market dynamics as possible. To segregate the results by size, the market capitalisation of commodity markets is based on the associated size of the futures market of the commodity product. This method is used as ETFs have been found to be more likely to invest on futures exchanges as a method of product creation. The size of the spot commodity market was also deemed unreliable due to the large variation in estimates. Larger commodity markets are usually more liquid, thus being more capable of absorbing the new large-scale investment. These markets are deemed to remain relatively unaffected and perhaps may even benefit from the added liquidity. The alternative is that ETFs have given 'noise traders' a useful platform to enter and exit commodity markets quickly and cheaply, with the transition of their risk-loving behaviour affecting commodity dynamics, thus adding to excess volatility.

Table 3.4 displays the estimated gamma coefficients based on the EGARCH investigations for each of the included ETFs investigated in this chapter. A more descriptive analysis of the results can be found in table AIV of the appendices. The associated commodity market is also included, and in situations where there are multiple investments for a single ETF, the date of fund initiation is investigated for each of the commodity market components invested. Figure 3.1 shows the relationship between EGARCH volatility and the size of the total ETF investment in each commodity market. There is a clear positive relationship between the two, but of particular interest is the fact that we can segregate the futures markets into positive and negative volatility estimates. In this situation, markets with a value of ETF investment under \$2.15 billion are associated with decreased EGARCH volatility post-introduction. This is indicative of large funds causing a detrimental volatility effect which has been attributed to the rebalancing process of these funds. This has also been pinpointed as problematic by the

CTFC[63] as ETFs with holdings above this threshold have the capability of dominating these commodity markets though size effects.

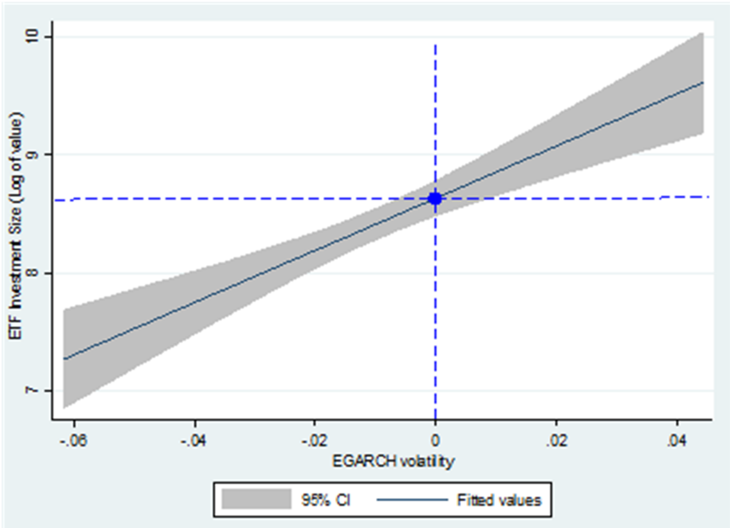
Table 3.4: *EGARCH(1,1) results for individual commodity ETFs under investigation*

ETF Ticker – Commodity	γ coefficient	ETF Ticker – Commodity	γ coefficient
SLV – Silver	0.001***	JJG – Wheat	0.029*
SIVR – Silver	-0.006**	JJG – Corn	0.019*
AGQ – Silver	-0.007*	DBC – WTI	-0.007
ZSL – Silver	-0.007***	DBC – Crude Oil	-0.008*
DBS – Silver	0.004**	DBC – Gold	0.012*
GLD – Gold	0.003**	DJP – Corn	0.025
IAU – Gold	0.004*	DBC – Corn	0.019*
SGOL – Gold	-0.008*	DBC – Natural Gas	-0.005*
UGL – Gold	-0.009**	DJP – Natural Gas	-0.001**
GLL – Gold	-0.009**	DBE – Gasoline RBOB	-0.005**
DBP – Gold	0.003**	BDG – Aluminium	0.936*
DGL – Gold	0.004**	DBE – Crude Oil	-0.005*
DGP – Gold	0.005*	DBE – WTI	-0.006*
UCI – Gold	-0.002*	DBC – Gasoline RBOB	-0.007*
DZZ – Gold	0.005***	BDG – Zinc	0.006***
DGZ – Gold	0.005***	DBC – Soybeans	-0.001
PGM – Platinum	0.021*	DBC –Wheat	0.019*
PTM – Platinum	0.020*	DJP – WTI	-0.007*
PPLT – Platinum	-0.011***	DJP – Soybeans	0.001
PALL – Platinum	-0.004***	DJP – Gold	0.012*
USO – WTI	-0.008*	DJP – Copper	0.001
DNO – WTI	-0.020*	DJP – Live Cattle	-0.029*
USL – WTI	-0.004	DJP – Wheat	0.021*
DBO – WTI	-0.006**	UGA – Gasoline RBOB	0.003***
OIL – Crude Oil	-0.006*	DBA – Live Cattle	-0.033*
UCO – Crude Oil	-0.009*	DBA – Coffee	0.013*
DTO – Crude Oil	-0.005**	DBA – Soybeans	0.002***
SCO – Crude Oil	-0.010*	DBA – Corn	0.021*
RJN – WTI	-0.004***	DBA – Wheat	0.022*
DBP – Silver	0.004***	DBA – Cocoa	0.137**
JJC – Copper	-0.001	DBA – Lean Hogs	0.013*
DBB – Aluminium	0.006*	DBA – Sugar	-0.008*
GAZ – Natural Gas	-0.002*	DBA – Feeder Cattle	-0.033*
UNG - Natural Gas	-0.005*	DBA – Cotton	-0.001
UNL - Natural Gas	-0.024**	BDG – Copper	0.001
JO – Coffee	-0.048***	RJA – Wheat	0.029*
SGG – Sugar	-0.003	RJA – Corn	0.019*
COW – Live Cattle	-0.016*	RJA – Soybeans	0.002***
COW – Lean Hogs	0.012*	JJG – Soybean	0.002***
RJA – Cotton	0.002		

Note: The above table gives the estimated γ coefficients for each investigated commodity market after the introduction of a new Exchange Traded Fund (ETF) based primarily on the investigated commodity market using the discussed EGARCH(1,1) methodology to investigate changes in volatility dynamics after ETF introduction. In the cases of multiple commodity investments for each ETF, the associated ticker and the commodity market invested are listed above. Robust standard errors for each result are marked in parentheses, where ***p<0.01, **p<0.05 and *p<0.10. The full associated EGARCH statistics and associated information based on each ETF investigated are found in table AIV of the Appendix.

[63] An statement made by the CFTC on the 20th of May 2011 specifically stated that the actions of a silver ETF was specifically responsible for market manipulation. 'CFTC signals open-season on silver market manipulation and NYSE:SLV ETF: *$500 million dollar payday on manipulated silver price takedown on COMEX futures market – CFTC commissioners continue their two and a half year ongoing investigation of silver price manipulation and illegal trading practices by the JP Morgan Chase and HSBC banks. All the while during the past three weeks, non-commercial traders added 6,000 new contracts to their silver short position. Then, utilizing computer automated High-Frequency-Trading (HFT) software, proceeded to flood the market with huge day-trading volume, equivalent to the entire annual silver mine production in a single day. Repeated daily HFT attacks within the last two weeks have resulted in a takedown of the COMEX spot price of silver by over 30 percent. Then, the same non-commercial traders bought back more than 8,300 silver contracts, netting $500 million dollars over the last three weeks'*.

Figure 3.1: *EGARCH volatility estimates and ETF investment size*



Note: Figure 3.1 shows the relationship between the EGARCH volatility estimates by commodity market investigated and the relative size of the total investment by the ETF. The shaded grey areas represent the 95% confidence intervals of the observations fitted values. We can clearly see a positive relationship (correlation coefficient of +0.63). The dashed blue lines represent the point at which EGARCH volatility switches from positive to negative, which occurs at a total ETF investment size of $2.15 billion. Thus markets under this value are associated with decreased volatility stemming from liquidity benefits from ETF investment, whereas those markets above this value are associated with increased EGARCH volatility.

3.4.2. GARCH investigation of the periods prior and post ETF introduction

The use of dummy variables in the short term EGARCH model caused significant issues when investigating low-liquidity commodity markets. One of the best methods to counteract this problem was to simply divide the investigation into two sections and investigate changes in the GARCH coefficients. This provided two testing periods where the resulting coefficients could be compared and analysed. The length of the periods examined offers stronger results about the dynamics involved. The same models were run as those used in the EGARCH investigation, but this led to significant estimation error, including negative coefficients and insignificance of the regressed variables. Investigating the coefficients offers interesting results. We can begin by looking at the persistence of shocks from the pre-ETF period to the post-ETF period, measured as $(\alpha_1 + \alpha_2)$. The second factor we can look at is β_1, where a decrease indicates a decrease in the autoregressive effect of returns, indicating that the market has increased its efficiency in the weak sense as proposed by Fama (1970). Finally we can look at the unconditional variance. We know that when the sum of α_1 and α_2 is less than one, the model has finite conditional variance h and it can be found by setting $E[\varepsilon_{t-1}^2] = h_t = h_{t-1} = h_0$. We can solve: $h_0 = \frac{\alpha_0}{1-\alpha_1-\alpha_2}$. The results of this analysis are found below in table 3.5, with a more descriptive analysis located in table AV in the appendices.

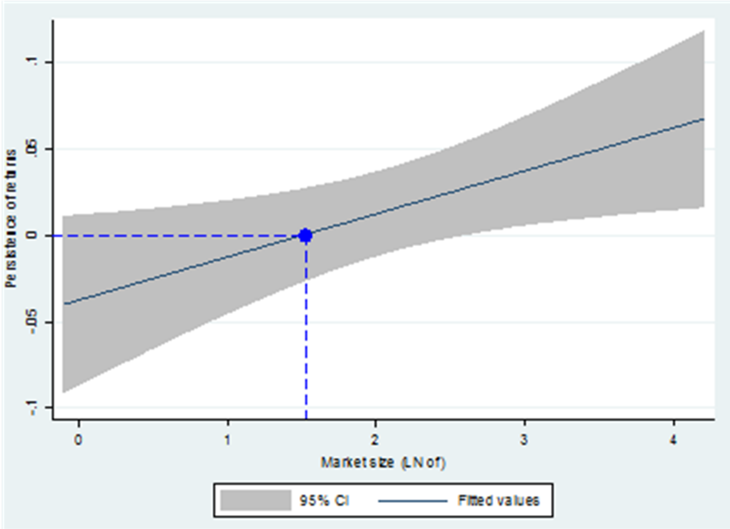
Table 3.5: *Efficiency statistics prior and post ETF introduction*

	Persistence		Autoregressive Effect		Unconditional Variance	
Exchange	**Pre-ETF**	**Post-ETF**	**Pre-ETF**	**Post-ETF**	**Pre-ETF**	**Post-ETF**
Silver (L)	0.990177	0.9776873	-0.1056	-0.0411	0.009823	0.022313
Gold (H)	0.920763	0.9984716	-0.1017	-0.0861	0.079237	0.0015284
Aluminium (L)	0.979963	0.9708763	-0.0444	-0.0544	0.020037	0.0291237
Brent Crude (H)	0.950943	0.9880818	-0.01873	-0.000845	0.0490567	0.01119182
Coffee (L)	0.8945685	0.9678022	-0.046149	-0.147227	0.1054315	0.0321978
Copper (L)	0.9967066	0.9795159	-0.0247	-0.0121	0.0032934	0.020484
Corn (H)	0.92132	0.9941834	0.0650166	0.0648505	0.07869	0.000251
Cotton (L)	0.9844124	0.971771	-0.114247	-0.16584	0.0155869	0.028229
Feeder Cattle (L)	0.995396	0.9908899	-0.01593	0.009174	0.004604	0.0091101
Gas. RBOB (H)	0.8892682	0.9813271	0.017513	0.046355	0.1107318	0.0186729
Lean Hogs (L)	0.9774973	0.9608197	-0.00636	0.063707	0.0225027	0.0391803
Live Cattle (H)	0.9953964	0.9908899	-0.015193	0.009174	0.004604	0.0091101
Natural Gas (H)	0.9062887	0.9952412	-0.142345	-0.041229	0.0937113	0.0047588
Palladium (L)	0.9939881	0.8099065	0.4447	0.0623	0.0060119	0.3900935
Platinum (L)	0.9924869	0.8632647	0.0190	-0.0301	0.0075131	0.136735
Soybeans (H)	0.9894918	0.9921701	-0.040481	0.020001	0.0105082	0.0078299
Sugar (H)	0.9102393	0.9942388	-0.001532	-0.0107760	0.0897607	0.0057612
Wheat (H)	0.9752514	0.990316	-0.001993	-0.042166	0.0231435	0.009684
WTI (H)	0.9568565	0.9884695	-0.015908	-0.001428	0.0005748	0.0115305
Zinc (L)	0.999879	0.9873626	-0.0212	0.0081	0.0007121	0.126374

Note: Table 3.5 shows the calculated statistics prior and post ETF introduction as calculated from the GARCH analysis. The main coefficients of interest are indicative of market efficiency and persistence ($\alpha_1 + \alpha_2$), the autoregressive effect of returns (β_1) and the unconditional variance (h_0). The results are taken from the GARCH models testing market conditions both before and after the introduction of ETFs.

The results can then be investigated and graphed based on market size. There are numerous interesting findings from the results. A reduction in persistence indicates a weak form increase in market efficiency. We can see that in 9 out of 10 cases, large commodity markets showed an increase in persistence between the pre-ETF and post-ETF period, which signifies a decrease in market efficiency. Alternatively, this only occurs once in the ten small-sized commodity markets investigated. This indicates that smaller commodity markets receive efficiency benefits after ETF investment. Larger commodity markets, though the ETF investment may not be proportionately as large in terms of total capitalisation levels, may in fact be losing efficiency based on a large influx of day traders and speculators, who are widely reported to be using ETFs as their investment tool of choice. There appears to be some threshold between large and small exchanges where ETF investment actually becomes counter-productive. From figure 3.2 below this is found to be in futures markets with a notional value of below $4.5 billion. This is based on regressions including both large and small commodity markets. Markets below this size threshold appear to benefit from increased liquidity.

Figure 3.2: *Market size and persistence of volatility changes pre and post ETF introduction*

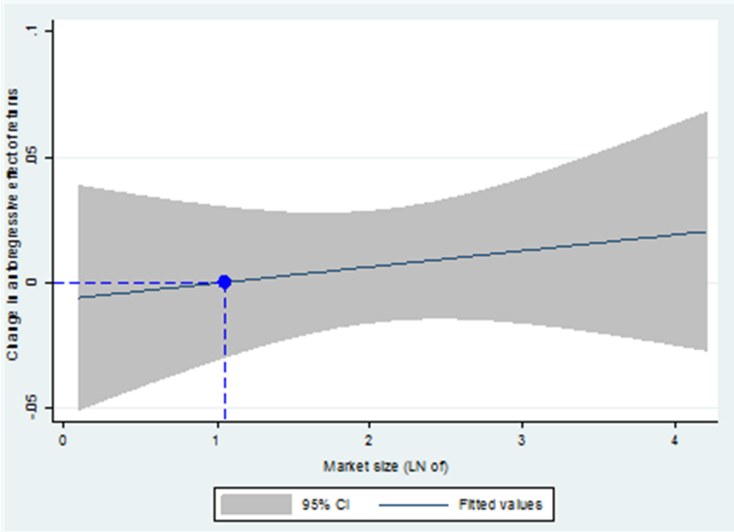


Note: Figure 3.2 represents the change in the level of persistence in the period prior and post-ETF introduction. We can clearly see a positive relationship (correlation of +0.51). This indicates that larger commodity markets are subject to increased persistence of volatility after the introduction of ETF investment. Alternatively, smaller markets under a value of \$4.5 billion approx. are subject to decreased persistence. The continued persistence in high capitalisation commodity markets may in fact be associated with the mass ownership of a large proportion of the market by one singular fund. This has been referenced as a problem by the CTFC since 2007.

The next feature investigated was the differences in the autoregressive effects between the pre and post-ETF periods. A decrease in β_1 post ETF GARCH analysis indicates a decrease in the autoregressive effect in returns, thus indicating a weak form improvement in market efficiency. In seven of the ten large market cases there was an increase in the autoregressive effect. This metric indicates a decrease in market efficiency after the introduction of ETFs. On the other hand, only five of the ten small commodity exchanges showed an increase in β_1. The results are difficult to compare, but it appears that smaller commodity exchanges benefitted more from the introduction of ETFs. Figure 3.3 shows a positive relationship between market size and the autoregressive effect of returns when modelled on all sizes of commodity markets. On average, markets under \$3 billion in size show increased efficiency under this metric.

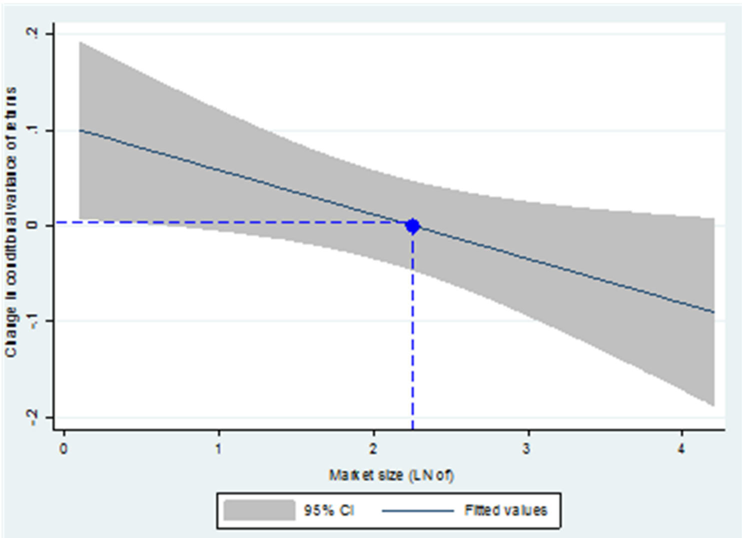
The final structural estimate is based on the unconditional variance. We know that when the sum of the $\alpha_1 + \alpha_2$ coefficient is less than one, the model has finite conditional variance h and it can be found by setting $E[\varepsilon_{t-1}^2] = h_t = h_{t-1} = h_0$. Then solving for $h_0$we can solve: $h_0 = \frac{\alpha_0}{1-\alpha_1-\alpha_2}$. In two of the ten large commodity markets investigated we can see an increase in conditional variance. Alternatively, in seven of the ten small commodity markets investigated we find an increase in the same metric. Thus, unconditional variance in small commodity markets increased more than that of their larger counter-parts. The results are found in figure 3.4.

Figure 3.3: *Market size and autoregressive effect of volatility changes pre and post ETF introduction*



Note: The autoregressive effect of returns operates under the premise that past values will have an effect on current values. From figure 3.3, we can see a positive relationship (+0.16) between market size and the chance in the autoregressive effect where larger markets have shown more of an increase. Markets below approximately $3 billion in size show a decrease in the effect, thus a weak-form improvement in efficiency. This can be linked with the increased liquidity levels found in these markets after the introduction of ETFs. Alternatively, larger commodity markets have been associated with increased likelihood that current returns have an influence on near term future returns.

Figure 3.4: *Market size and unconditional variance changes pre and post ETF introduction*



Note: Unconditional variance quantifies uncertainty about the future observation given everything we have seen so far. This is of practical interest when forecasting. From figure 3.4 we can see a negative relationship (-0.48) between market size and the change in conditional variance, where commodity markets with a value below $9.5 billion have increased unconditional variance indicative of more significant short term uncertainty. Markets above this level have seen a significant increase in the same metric indicative of an improvement in liquidity levels from ETF investment.

Overall, smaller markets showed an increase in efficiency from the new flow of funds originating from ETFs, though the unconditional variance of these same markets increases significantly. Larger markets showed a reduction in efficiency but lower unconditional variance in returns. This may have stemmed from the increased flow of noise traders that entered the market from the new cheap and efficient trading platforms that ETFs provided. These findings support the CFTC's views that large funds are having a dominant effect in large commodity markets. Alternatively, smaller markets appear to have benefitted from increased liquidity but the negative effects of numerous traders quickly entering and exiting positions through ETFs may be increasing volatility through the rebalancing process, thus contributing to increased variance.

3.4.3. A four moment analysis of commodity volatility after ETF introduction

A four moment analysis shows some interesting dynamic shifts in commodity markets from the pre-ETF to post-ETF period. The four moments (mean, variance, skewness and excess kurtosis) are compared from the pre-ETF and post-ETF period, with the nominal changes between the two periods compared with market size to investigate structural difference. We then graph the statistics based on the market size of each market to investigate any stylized facts available. The results are found in table 3.6.

Table 3.6: *Four moment analysis statistics of the commodity markets investigated*

	Mean		Variance		Skewness		Excess kurtosis	
Exchange	**Pre-ETF**	**Post-ETF**	**Pre-ETF**	**Post-ETF**	**Pre-ETF**	**Post-ETF**	**Pre-ETF**	**Post-ETF**
Silver (L)	-0.0398	-0.0171	0.02411	0.0575	2.4222	1.3743	31.8167	8.6518
Gold (H)	-0.02918	-0.05159	0.00086	0.01975	-0.3577	0.2799	4.77093	4.74098
Aluminium (L)	0.00249	-0.0322	0.01157	0.03335	-0.6296	-0.2696	5.11555	0.87743
Brent Crude (H)	0.02980	-0.019676	0.05742	0.076706	-0.79337	-0.10643	4.13313	4.40347
Coffee (L)	-0.00559	-0.000329	0.052246	0.028955	-0.29745	-0.67321	7.14169	3.08034
Copper (L)	0.034982	-0.071266	0.015964	0.056554	-0.45394	-0.18619	5.59671	1.77962
Corn (H)	-0.04182	0.030754	0.050204	0.051612	-0.39569	-1.00086	3.55113	7.24138
Cotton (L)	-0.01538	-0.35105	0.048804	0.025701	-0.92530	-2.56830	25.8978	91.89338
Feeder Cattle (L)	0.011068	0.014439	0.005229	0.005762	-0.98981	-0.53229	11.66357	2.500751
Gas. RBOB (H)	0.059000	-0.01984	0.090541	0.083133	-0.44183	-0.14649	7.331363	2.447162
Lean Hogs (L)	0.034385	0.000462	0.013738	0.016915	-0.47490	-0.18077	3.296428	2.094797
Live Cattle (H)	0.011068	0.014439	0.005229	0.005762	-0.98981	-0.53229	11.66357	2.500751
Natural Gas (H)	0.121986	-0.07963	0.011395	0.017578	0.001662	-0.075787	1.69740	1.46162
Palladium (L)	-0.02721	0.13361	0.05076	0.04952	-0.58186	-1.04613	5.03719	2.81861
Platinum (L)	0.03591	0.02279	0.02454	0.01466	-0.66818	-1.09715	5.69051	3.80930
Soybeans (H)	0.005909	0.004571	0.024512	0.038119	-0.75043	-0.48793	14.81891	2.074308
Sugar (H)	0.012381	-0.001753	0.038932	0.054443	-0.28978	-0.35269	1.481547	1.404812
Wheat (H)	0.025998	-0.043919	0.033976	0.085467	0.295041	-0.34354	2.086856	2.386291
WTI (H)	0.031509	-0.02195	0.056799	0.076335	-0.78746	-0.105517	4.116368	4.466692
Zinc (L)	-0.012238	-0.053751	0.014669	0.063684	-0.402122	-0.189758	3.762914	1.218715

Note: Table 3.6 above reports the findings of the four moment analysis comparing volatility dynamics in the period prior and post-ETF introduction. The reported coefficients are based on the average introduction, across all ETFs introduced, by commodity market investigated.

It is also possible to investigate the four moment reactions of commodity markets in the period before and after the introduction of the ETFs investigated in this chapter. This can be found in table 3.7. We can clearly see that there are small differences present between some observations given the close proximity of inception dates in some cases. There are also inception dates associated with multiple fund introductions in the same commodity markets. These funds are simply joined together for a more simple representation.

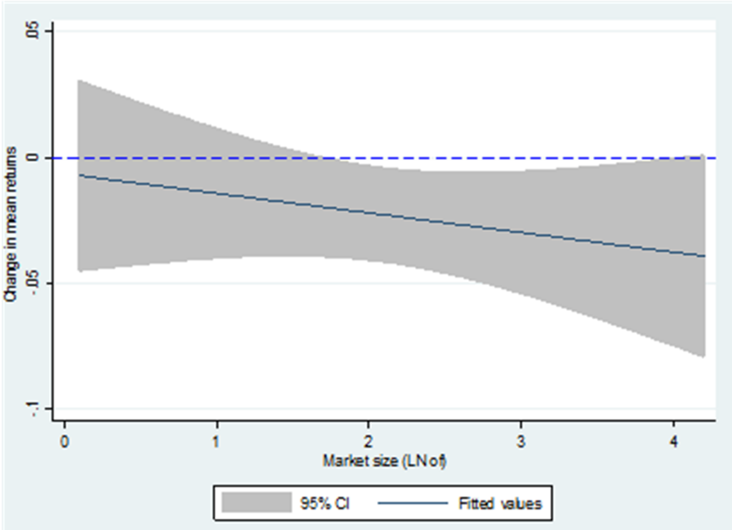
Table 3.7: *Four moment analysis statistics before and after specific ETF introduction*

			Mean		Variance		Skewness		Excess kurtosis	
ETF	Inception date	Commodity	Pre-ETF	Post-ETF	Pre-ETF	Post-ETF	Pre-ETF	Post-ETF	Pre-ETF	Post-ETF
JO	25/6/2008	Coffee	0.00033	0.00038	0.00058	0.00028	-0.0042	-0.1050	9.6581	1.7459
JJC	23/10/2007	Copper	0.00080	0.00029	0.00023	0.00049	0.0145	0.0140	5.4745	2.4306
GLD	18/11/2004	Gold	0.00038	0.00074	0.00007	0.00017	0.4432	-0.3111	6.7789	3.3878
IAU	28/1/2005	Gold	0.00032	0.00079	0.00007	0.00017	0.3630	-0.3056	6.7492	3.3285
DBP, DGL	5/1/2007	Gold	0.00045	0.00079	0.00009	0.00018	-0.068	-0.2423	4.9806	3.4318
DGP, DZZ, DGZ	28/2/2008	Gold	0.00061	0.00056	0.00009	0.00021	-0.1277	-0.1897	4.3834	3.2162
UCI	1/4/2008	Gold	0.00059	0.00061	0.00010	0.00020	-0.2194	-0.1363	4.7305	3.1355
UGL,GLL	3/12/2008	Gold	0.00049	0.00088	0.00013	0.00016	-0.2022	-0.1432	5.3352	3.0437
SGOL	9/9/2009	Gold	0.00056	0.00074	0.00013	0.00013	-0.034	-0.7111	5.0942	2.5674
UNG	18/4/2007	Natural gas	0.00168	-0.0002	0.00214	0.00153	0.6658	1.44895	5.5630	13.598
GAZ	23/10/2007	Natural gas	0.00155	-0.00015	0.00209	0.00156	0.6615	1.53824	5.5450	14.478
UNL	18/11/2009	Natural gas	0.00119	-0.00014	0.00209	0.00107	0.7850	2.03437	6.6612	19.019
PALL	8/1/2010	Palladium	0.00025	0.000895	0.00054	0.00052	0.1089	-0.38907	5.9703	1.7866
PTM	9/5/2008	Platinum	0.00081	-0.0002	0.00021	0.00030	-0.7199	-0.6007	13.467	3.4131
PGM	25/6/2008	Platinum	0.00077	-0.00016	0.00021	0.00035	-0.7403	-0.6167	13.644	3.5061
PPLT	8/1/2010	Platinum	0.00061	0.00002	0.00026	0.00016	-0.6991	-0.6115	9.0625	2.0287
SLV	28/4/2006	Silver	0.00065	0.00091	0.00024	0.00072	-0.7596	-0.0569	10.075	6.9315
DBS	5/1/2007	Silver	0.00064	0.00097	0.00029	0.00072	-0.7229	0.00468	8.5728	7.5886
AGQ, ZSL	3/12/2008	Silver	0.00044	0.00165	0.00037	0.00075	-0.2941	-0.1161	11.875	6.2868
SIVR	24/7/2009	Silver	0.00058	0.00144	0.00038	0.00078	-0.2270	-0.1484	10.211	7.1381
USO	10/4/2006	WTI oil	0.00089	0.00057	0.00061	0.00067	-0.4029	0.3234	2.9562	5.6698
OIL	15/8/2006	WTI oil	0.00089	0.00053	0.00059	0.00069	-0.3977	0.3289	3.0073	5.5731
DBO	5/1/2007	WTI oil	0.00072	0.00075	0.00057	0.00072	-0.3839	0.3240	3.0070	5.4717
USL	6/12/2007	WTI oil	0.00087	0.00049	0.00055	0.00076	-0.3705	0.3469	3.0164	5.1853
UCO	25/1/2008	WTI oil	0.00087	0.00047	0.00054	0.00081	-0.3625	0.3438	3.0111	5.1261
DTO	17/6/2008	WTI oil	0.00102	0.00005	0.00054	0.00084	-0.3395	0.3612	2.9549	5.1484
SCO	25/11/2008	WTI oil	0.00059	0.00109	0.00060	0.00072	-0.2181	0.3701	3.8671	5.3147
DNO	24/9/2009	WTI oil	0.00074	0.00069	0.00071	0.00037	-0.0246	0.0307	4.1975	2.5109

Note: Table 3.7 above reports the findings of the four moment analysis comparing volatility dynamics in the period prior and post-ETF introduction. The reported coefficients are based on the ETFs introduced and the specific commodity market the ETF entered. In the case of ETFs with multiple underlying securities, only investments above 40% of the underlying asset base of the investigated ETF are included. In some cases, ETFs had the same inception date in the same commodity market, therefore, they are combined together to shorten the analysis.

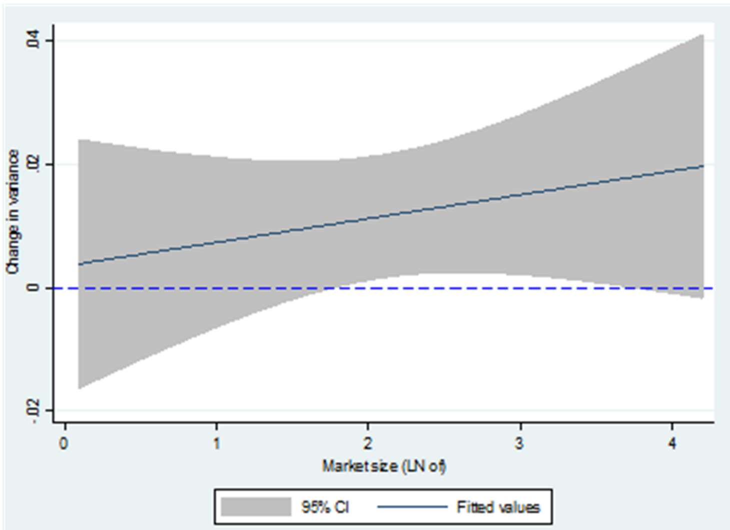
From figures 3.5 and 3.6, we find that mean volatility is negative after the introduction of ETFs and the variance is positive. Smaller markets are associated with smaller means and variance of volatility in the same returns indicating reduced effects from ETF investment on volatility and market efficiency. The same cannot be said for larger markets, which show significantly larger effects in the same metrics. The skewness and excess kurtosis of the same markets also show significant differences in the pre and post-ETF periods and are modelled in figures 3.7 and 3.8. The results indicate that markets below $12.2 billion in size show negative skewness after ETF introduction and below $33.1 billion show negative excess kurtosis. Therefore, only the smallest markets appear to be influenced most significantly, but it does appear that there is a specific size limit of the commodity markets investigated that allows for the efficient absorption of the liquidity flows from these new ETFs. The flight to safety in oil and gold markets have significantly contributed to these findings and ETFs were a prime platform for all market participants to quickly enter and exit their positions leading to higher positive values in the skewness and kurtosis of returns. These findings further support the view that larger commodity markets have been subjected to increased speculation and decreased efficiency since the inception of ETFs.

Figure 3.5: *Market size and mean volatility pre and post ETF introduction*



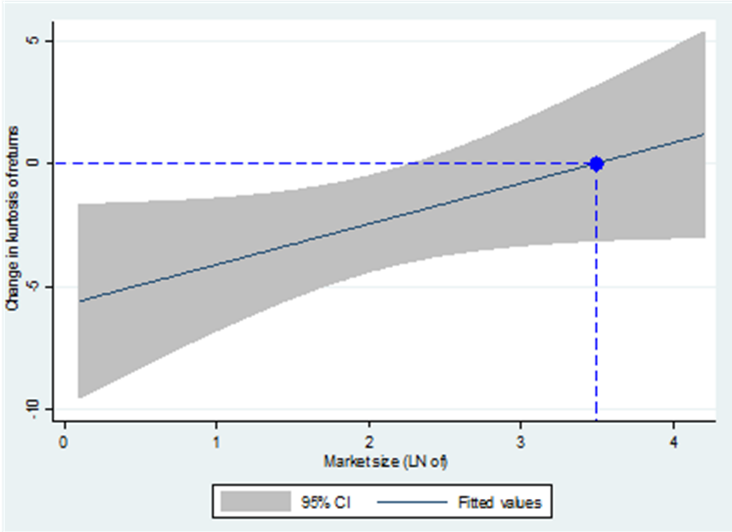
Note: Though negatively correlated (-0.23), mean volatility as a whole decreased throughout all sized commodity markets in the period after ETF introduction. The negative correlation indicates that larger markets are associated with volatility decreases than smaller markets after ETF introduction (as measured by the change between the period before and after ETFs), again adding more weight to the argument that ETFs may have had more impact stabilising these markets through added liquidity.

Figure 3.6: *Market size and the variance of return volatility pre and post ETF introduction*



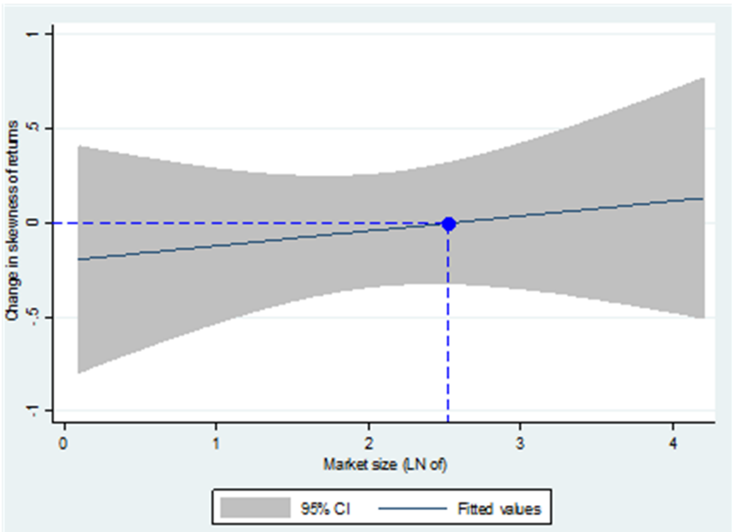
Note: Volatility appears to have increased in the period after ETF introduction across all sized markets, though the positive correlation (+0.21) indicates that larger markets experienced more. This indicates that there were more drastic swings in intraday volatility in daily large market volatility, though combining this with figure 3.6 shows that on average, the mean of this level of return was larger than smaller markets.

Figure 3.7: *Market size and the skewness of return volatility pre and post ETF introduction*



Note: There is a slight positive correlation (+0.13) between the change in skewness and commodity market size. From figure 3.7, we can see that there is more negative skewness associated with smaller markets and higher skewness with larger markets. In this case smaller markets are more likely to have negative returns and larger markets have positive returns after the introduction of ETFs. The breakeven point in the analysis is approximately markets over $12.2 billion.

Figure 3.8: *Market size and the excess kurtosis of return volatility pre and post ETF introduction*



Note: The change in kurtosis of larger markets is also found to increase significantly for those futures markets over approximately over $3.1 billion in value. The probability of periods of drastic volatility changes therefore decreases significantly in these markets offering evidence towards the view that ETFs stabilised larger markets. Alternatively, smaller markets are associated with an increased probability of spurious returns after the initiation of ETF investment, thus offering evidence against their investment capabilities in these products.

3.5. Conclusions

Exchange traded funds (ETFs) have grown in recent years to become one of the most commonly used investment techniques across international financial markets. The diversification, leverage and ease of use have attracted numerous international investors. This chapter investigates whether commodity ETFs amplified or influenced volatility in the period after their introduction.

The main findings in this chapter indicate large differences in volatility between large and small commodity markets in the period after ETF introduction. Larger ETF investments are found to be associated with increased EGARCH volatility. This supports numerous regulatory views (CFTC among others) that some ETFs are having dominant effects on the markets in which they invest. Smaller commodity markets are found to have increased efficiency as measured by weak-form metrics such as persistence and the autoregressive effect. This finding supports the view that liquidity benefits appear to be present in markets below $4 to $5 billion in size. One downside is the accompanying increase in unconditional variance which stems from the increased transaction numbers from the rebalancing process of these ETFs. The four moment analysis supports the view that larger markets as a whole appear to have decreased in efficiency and increased in risk stemming from the large-scale inflow of noise traders. The dummy variable used in the EGARCH model appears significantly positive at 55% of the ETF introduction scenarios investigated in this paper. 28% of the ETFs investigated show significantly negative EGARCH volatility whereas 17% of the results were insignificant. Overall, it appears that ETFs have made commodity markets more efficient through new trading counterparties, but they are also associated with more EGARCH volatility. The potential negative market-dominating impacts associated with ETFs and their re-balancing processes cannot be rejected.

These findings support calls for more intense regulation of the ETF industry and more investigation into the investment practices and rebalancing processes of the funds in question. The need for regulation of investment size and the imposition of market ownership caps cannot be rejected.

Chapter 4: Financial market liquidity and its association with episodes of financial stress

Abstract: *Understanding the structural changes in liquidity in Europe is important for macroprudential risk assessment, as sudden changes in conditions may be indicative of current stress and a signal of future stress. This chapter presents a European-specific liquidity measure used by several central banks, with some modifications. The measure is constructed by combining numerous facets of liquidity and depth measurement across several asset markets. It attempts to incorporate aspects such as market tightness, depth and resiliency. The flows and the direction of causality of liquidity can also be inferred using vector autoregression, Granger causality and impulse response functions. The time series of the liquidity measure over the period 1999-2011 is analysed. It is found that liquidity has moved out of traditionally 'safer' assets into those of higher-risk due to large volatility changes across numerous international exchanges such as sovereign bonds and commodities, particularly during the period between 2008 to 2010.*

4.1. Introduction

The creation of the Eurozone in 1999 marked an historic event in monetary history as fourteen diverse nations joined together to create a single currency. This chapter investigates liquidity in the Eurozone since its establishment and the informational components present in its construction, which may be indicative of current stress and signals of future stress. Using a model of financial market liquidity measurement in this chapter, it is possible to investigate the stylised facts associated with investor behaviour during periods of growth, relative stability and crisis.

Market liquidity is defined as the ease with which an asset can be traded. By further investigating this, it may be possible to trace investor flows between assets, as liquidity shifts between asset classes based on the trading activity and perceptions of the international financial markets. The basic model used in this chapter was developed by the Bank of England and was further developed by the European Central Bank. This chapter develops the model still further through the addition of commodity market liquidity flows to take account of 'flights to safety' that occur during periods of crisis in equity and currency markets. The indicator can be used to investigate the mass movements of investors during the events of the twelve year period since the euro's inception and to test the behaviour of participants in the selected markets. Numerous changes in market structure such as disintegration of trading barriers, the reduction of trading costs and the introduction of derivatives have created a new investment environment in Europe. Understanding this behaviour is a key to offering pre-emptive information regarding oncoming stresses and pressures in European markets.

Investors choose to move or divide their assets among asset classes based on their risk preferences. Investigating the cause and effect dynamics between these markets using vector autoregression[64] (VAR) offers an insightful picture of the mass movements of investors in European markets while simultaneously measuring the risk seeking and avoiding behaviour of these investors in differing market situations. Movements between asset classes based on the risk perceptions of investors can also be traced using Granger causality[65] and impulse response function[66] (IRF) analysis.

Section 4.2 reviews a few papers with particular relevance to this chapter. In section 4.3, the methodology behind the creation of this version of the European financial market liquidity indicator is developed and extended. It includes an indicator based on commodity markets to measure 'flights to safety' that are found to occur in periods of equity market stress. A detailed analysis of the models used to test the dynamics of the integration between the variables in the liquidity indicator is also presented in section 4.3. Section 4.4 presents the results of the liquidity investigation during the period 1999-2010 and compares the indicator developed in this chapter to other metrics of financial stress. The results of the Granger analysis, VAR and IRF analysis are also presented while section 4.5 offers the main conclusions of the chapter.

In comparison to European Credit Default Swaps and EBA[67] banks' probabilities of default (PD), the indicator is found to compare well, with distinct periods of banking crises occurring in tangent with periods of large liquidity falls. It is however overshadowed by data issues, such as the lack of information available on bond markets. The correlations of returns between the differing channels of investment-methods in Europe are found to have changed significantly since the emergence of international crisis. A combination of Granger causality, vector autoregression and impulse response functions uncovered strong reactions among particular channels of the liquidity indicator. A large movement out of equities and into currencies is evident in the period between 2006 and 2010 as investors became sceptical about the health of numerous international financial companies.

[64] Vector autoregression (VAR) is an econometric model used to capture the evolution and the interdependencies between multiple time series, generalizing the univariate AR models. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. Based on this feature, Christopher Sims advocates the use of VAR models as a theory-free method to estimate economic relationships, thus being an alternative to the "incredible identification restrictions" in structural models.

[65] The Granger causality test is a statistical hypothesis test for determining whether one time series is useful in forecasting another. Ordinarily, regressions reflect "mere" correlations, but Clive Granger, who won a Nobel Prize in Economics, argued that there is an interpretation of a set of tests as revealing something about causality. A time series X is said to Granger-cause Y if it can be shown, usually through a series of t-tests and F-tests on lagged values of X (and with lagged values of Y also included), that those X values provide statistically significant information about future values of Y.

[66] In signal processing, the impulse response, or impulse response function (IRF), of a dynamic system is its output when presented with a brief input signal, called an impulse. More generally, an impulse response refers to the reaction of any dynamic system in response to some external change.

[67] The European Banking Authority (EBA) was established by Regulation (EC) No. 1093/2010 of the European Parliament and the Council of 24th November 2010. The EBA officially came into being as of the 1st of January 2011 and has taken over all the existing and ongoing tasks and responsibilities of the Committee of European Banking Supervisors (CEBS). It specifically acts as a hub and spoke network of EU and national bodies safeguarding public values such as the stability of the financial system, the transparency of markets and financial products and the protection of depositors and investors.

4.2. Previous literature

A liquid asset can be sold rapidly with minimal loss of value at any time. The essential characteristic of a liquid market is that there are ready and willing buyers and sellers at all times. A market may be considered deeply liquid if there are ready and willing buyers and sellers in large quantities. This is related to the concept of market depth that can be measured as the number of units that can be sold or bought for a given price impact. A related concept is that of market breadth measured as the price impact per unit of liquidity as measured by the return to volume ratio. An illiquid asset is an asset which is not readily saleable due to uncertainty about its value or the lack of depth in the market in which it is regularly traded.

Amihud et al. (2005) believe that liquidity can play a role in resolving a number of asset pricing puzzles such as the small-firm effect, the equity premium puzzle and the risk free rate puzzle. Lo et al. (2004) find that the liquidity premium can be large when the investors have high-frequency trading needs. Brunnermeier and Pedersen (2005) relate variations in liquidity over time and cross-sectionally to market makers' capital constraints. Duffie et al. (2003) link volatility to liquidity and thus to prices. Weill (2002) and Vayanos and Wang (2002) extend the model of Duffie, Garleanu and Pedersen to the case of multiple illiquid securities and show, among other things, that search frictions lead to cross-sectional differences in the liquidity premium. Amihud (2002) examines the effect of illiquidity on the selected cross-section of stock returns using an illiquidity measure that is related to the Kyle (1985) price impact model. The results show that illiquidity has a positive and significant effect on stock returns.

If liquidity affects asset prices, it stands to reason that changes in liquidity should change asset prices, which is examined by Amihud et al. (1991). The authors suggest that the stock market crash of October 19, 1987 can be partly explained by a decline in investors' perception of the market's liquidity. They regress cross-sectionally the risk-adjusted returns of NYSE stocks that are included in the S&P 500 index on October 19, 1987 on the change in liquidity during that day, measured by the average daily bid–ask spread or by depth[68]. The results show that stocks that suffered the greatest decline in liquidity on that day also suffered the greatest decline in prices. Further, stocks whose liquidity recovered more by the end of the month also enjoyed a greater recovery in price. Amihud et al. (1997) find that their trading volume increased significantly relative to the market and their liquidity ratio[69] declined. Consequently, the prices of the equities increased by at least 5% to 6% and

[68] The bid–ask spread for securities (such as stocks, futures contracts, options, or currency pairs) is the difference between the prices quoted (either by a single market maker or in a limit order book) for an immediate sale (ask) and an immediate purchase (bid). The size of the bid-offer spread in a security is one measure of the liquidity of the market and of the size of the transaction cost. Market depth is the size of an order needed to move the market by a given amount. If the market is deep, a large order is needed to change the price. Market depth closely relates to the notion of liquidity, the ease to find a trading partner for a given order: a deep market is also a liquid market.

[69] The reserve requirement is a central bank regulation that sets the minimum reserves each commercial bank must hold of customer deposits and notes. It is normally in the form of cash stored physically in a bank vault or deposits made with a central bank. The reserve ratio is sometimes used as a tool in the monetary policy, influencing the country's borrowing and interest rates by changing the amount of loans available. Western central banks rarely alter the reserve requirements because it would cause immediate liquidity problems for banks with low excess reserves; they generally prefer to use open market operations to implement their monetary policy.

remained high. Similar results are obtained by Muscarella and Piwowar (2001) for the Paris Bourse's transfer of stocks from a call to a continuous market, and by Kalay et al. (2002) for a later improvement in the trading system at the Tel Aviv Stock Exchange. In a cross-section analysis, Berkman and Eleswarapu (1998) found that the decline in prices of Badla stocks was significantly associated with the decline in their liquidity. Hedge and McDermott (2003) document increases in the liquidity of stocks that are added to the S&P 500 index, with liquidity being measured in a number of ways including the bid–ask spread (quoted and effective), volume, and trading frequency. The authors find that the price increase of added stocks is positively and significantly associated with the improvement in liquidity. Angel et al. (2005) examine stocks that are involuntarily delisted from the Nasdaq Stock Market and are subsequently traded in the OTC Bulletin Board and in the Pink Sheets. They find a large and significant deterioration in liquidity, measured by trading volume, number of quotes per day and the bid–ask spread and a large and significant price decline of about 18% around the delisting day.

Bessembinder and Seguin (1993) investigated the link between volatility, volume and market depth, using data from the futures market. They found that when volume is broken into anticipated and unanticipated components, the unanticipated volume shock has a larger effect on price volatility. Gervais, Kaniel and Mingelgrin (1998) investigated the 'high volatility return premium'. The main finding in this paper is that stocks experiencing unusually high (low) trading volume over a period of one day to a week tend to appreciate (depreciate) over the course of the following months. Bollerslev and Jubinski (1999) focused also on equity trading volume and volatility, focusing particularly on latent information arrivals and common long-run dependencies. The authors found that shocks to both volume and volatility processes are persistent and that the same shocks evenly dissipate at the same hyperbolic rate of decay. Wu and Guo (2004) investigated the link between asset price volatility and trading volume and show a positive relationship between trading volume and the direction of price changes. Kaproff (1987) showed that there is a positive relationship between trading volume and the direction of price changes, similar to a positive relationship between volume and the magnitude of price changes. Brailsford (1996) found the relationship between stock volatility in Australia and trading volume to be significantly positive irrespective of the direction of the price change. Chan and Fong (1999) using data from the NYSE and NASDAQ confirmed the significance of the theory that the size of trades influences the volume-volatility relationship more than that of the number of trades. The authors also find that the order imbalance has explanatory power in the relationship. Galati (2000) investigated volume, volatility and spreads in foreign exchange markets to find that unexpected volume and volatility are positively related.

4.3. Data, methodology and structure of the models

The financial market liquidity indicator was first developed by the Bank of England for its financial stability review[70] and was further developed by the European Central Bank[71]. The main liquidity measures consist of the bid-ask spreads, the return to volume ratio and numerous measures of liquidity premia[72]. To replicate this measure, this chapter includes the individual measures included in table 4.1.

The ECB and BOE produce a liquidity indicator specifically based on equity, bond, currency and interest rate markets. The indicator developed here adds the bid-ask spread across an average of eight commodity markets in an attempt to measure 'flights to safety' out of alternative assets. This composite measure is designed to capture the key elements and patterns in financial market liquidity. It is constructed by combining information across several markets – covering foreign exchange, fixed income, equities, commodities and credit across three dimensions of liquidity including tightness, depth and resiliency, as well as estimates of liquidity premia. These elements are defined as:

a) Tightness is the magnitude of the risk premiums required by market makers for holding inventories of securities and is usually gauged by the width of the bid-ask spreads
b) Depth and resiliency are the degree to which trading affects asset prices which can be gauged using ratios of price movements to transactions in the relative markets
c) Liquidity risk premia are the compensation required by investors for the risk present when they attempt to exit their positions. It can be measured using various spreads between securities which are known to have varying degrees of liquidity.

Table 4.1: *Liquidity measure components included in the creation of this indicator*

Bid-ask spreads	- Exchange Rates (EUR/USD, EUR/JPY, EUR/GBP) - Eurostoxx 50 (The average spread of the individual exchange components) - EONIA 1 month and 3 month swap rates
Return to volume ratio	- Equity market return to volume ratio - The Euro bonds market return to volume ratio - The equity options market (S&P 500 options used as a proxy)
Liquidity premia	- Spreads on euro area high yield bonds - Euro area spreads between interbank deposit and repo interest rates
Commodities	- Bid-ask spreads averaged on the markets for WTI oil, crude oil, gold, silver, copper, platinum, aluminium and palladium

Note: The above variables combined together as an unweighted average represent the European financial market liquidity indicator. The data used to attain this indicator was extracted from Bloomberg and Thompson Reuters DataStream.

[70] Bank of England Financial Stability Review, April 2007, Box 2, Page 18
[71] European Central Bank Financial Stability Review, June 2007, Box 9, Page 81
[72] The liquidity premium is a term used to explain a difference between two types of financial securities that have all the same qualities except liquidity.

The indicator initially used by the ECB and BOE simply uses the un-weighted average of these individual indicators. Some caveats apply. The first is the availability of data. Some data used previously in the indicators are publicly unavailable at the time of writing this chapter. Some proxies have to be used as estimators of the original dataset. The data need to be standardised to take into account differing trends across the time period investigated and also to deal with the problem of the averaging of different nominal values throughout the indicator.

According to the European Central Bank, there are numerous factors that have increased financial market liquidity. One factor, supported by ECB research is that the growth in monetary aggregates exceeding that of nominal economic growth for some time may have bid asset prices upwards. Another factor is based on the reserve accumulation of the Asian central banks and oil producing countries has raised the number of and the diversity among market participants in mature-economy financial markets. There has also been an increase in the risk appetite of market agents after the creation of the Eurozone, which appears to have been built on the confidence that the union would successfully integrate. Another positive influence on liquidity stemmed from the structural changes which have been taking place in financial markets. These have included the liberalisation of international capital flows, the securitisation of loans and the development of new financial products (for example, credit derivatives). Simultaneously, the emergence and growing presence of highly active participants such as investment funds and hedge funds in financial markets has provided enhanced market liquidity. These developments appear to have affected the greater degree of heterogeneity of investors that trade European financial products, as the withdrawal of trading barriers, efficiency improvements and increased confidence in European markets has attracted new investors from both inside and outside Europe.

The European financial market liquidity indicator is based on nine individual components representing market liquidity. It covers the tightness, depth, resiliency and liquidity risk premiums associated with a market. The first investigated component is the bid-ask spread, which is associated with the tightness of the market. The spread itself is divided by the midpoint of the product’s price to take account of differences in the nominal price of the products under investigation. The spread is:

$$Bid - ask\ spread = \sum_{i}^{N=n} \frac{Ask\ Price - Bid\ Price}{Midpoint}$$

The total bid-ask indicator (BAI) for the three different individual elements included in the indicator can be calculated as:

$$BAI = \sum_{i}^{N=3} \frac{A_{ci} - B_{Ci}}{A_{ci}} + \sum_{i}^{N=50} \frac{A_{ESTX50i} - B_{ESTX50i}}{A_{ESTX50i}} + \left(\frac{\frac{A_{EONIA(1mth)i} - B_{EONIA(1mth)i}}{M_{EONIA(1mth)i}} + \frac{A_{EONIA(3mth)i} - B_{EONIA(3mth)i}}{M_{EONIA(3mth)i}}}{2} \right)$$

where A represents the ask price, B is the bid price and M is the midpoint price at time t. C is the average of the currency markets investigated which are the markets for Euro-Dollar, Euro-Sterling and Euro-Yen cross currency values.. The middle term above is the average bid-ask spreads for all elements of the Eurostoxx 50, while finally we look at the average bid-ask spread of the 1 and 3 month EONIA swap rates. The average of the bid-ask spreads on the Eurostoxx 50 represents European equity market tightness, while the inclusion of bid-ask spreads on the EONIA 1 and 3 month swap rates focus on the tightness of European interest rate markets.

The second component is based on the depth and resiliency of the market and focuses on the return to volume ratios for the Eurostoxx 50 as a measure of European equities, the European bond markets and the equity options market. Though some markets do not have an active options market, the implied volatility of the exchanges serves as a good proxy. It is defined as:

$$ILLIQ_{\mathrm{Q}} = \frac{|\mathrm{R_{iyd}}|}{\mathrm{VOLD_{iyd}}}$$

where $|\mathrm{R_{iyd}}|$ is the return on stock i on day d of year y and $\mathrm{VOLD_{iyd}}$ is the respective daily volume after being converted from US dollars ($) to euros (€). The ratio gives the absolute percentage price change per euro of daily trading volume, or the daily price impact of order flow. The return to volume ratio (RtoV) in this indicator can be defined as the combination of the listed factors above:

$$R\ to\ V = \left(\sum_{i}^{N=50} \frac{\frac{R_{t-1} - R_t}{R_{t-1}}}{Volume_{ESTX50i}} \right) + \left(\sum_{i}^{N=2} \frac{\frac{R_{t-1} - R_t}{R_{t-1}}}{Volume_{Deutsche\ Boersei}} \right) + \left(\frac{\sigma_{ESTX50i} - \sigma_{VIXi}}{\log(Volume_{ESTX50i})} \right)$$

where R is the return at time t and time t-1, and σ the implied volatility of both the Eurostoxx 50 and the VIX[73] in the United States. The VIX is subtracted to give an estimate of European specific implied volatility. $Volume_{ESTX50}$ is representative of the volumes traded on the Eurostoxx and $Volume_{Deutsche\ Boerse}$ is used as a proxy for bond data as traded on the Deutsche Boerse. In situations where liquidity flows outwards, the market is deemed to lose efficiency – which is measured as a reduction of the individual components of the indicator. Alternatively, when liquidity flows inwards, the market is said to gain efficiency, thus measures such as the bid-ask spreads for example, become smaller. Even though the nominal value of volumes traded may not be available, a proxy for this figure may be inferred from the efficiency of the market as a whole. The liquidity premia (LP) element is based on the indicators of the spreads on European high yield bonds and the spreads between the European interbank deposit rate and repo interest rates.

$$\text{Liquidity Premia (LP)} = (\text{High yield Euro. Corp. Bonds} - \text{Low Yield Euro. Corp. Bonds}) + (\mathrm{EURIBOR}_t - \mathrm{EUREPO}_t)$$

Commodity liquidity is added as an additional liquidity variable in this liquidity indicator model. When a crisis disrupts markets such as equity and currency markets, investors have traditionally moved to commodity markets as a method of hedging risk. The commodity indicator is developed based on the average bid-ask spread of the spot market prices for all the commodities listed in table 4.1. Commodity market liquidity is included to indicate a

[73] VIX is the ticker symbol for the Chicago Board Options Exchange Market Volatility Index, a popular measure of the implied volatility of S&P 500 index options. Often referred to as the fear index or the fear gauge, it represents one measure of the market's expectation of stock market volatility over the next 30 day period. The VIX Index was introduced by Prof. Robert Whaley in 1993.

phenomenon known as a ‘flight to safety’. This occurs when crises and panic occur in financial markets, therefore investors tend to invest in commodity markets for shelter from this increased risk. In the financial crises since 2007, gold prices increased over 600% and oil prices over 500%. This also occurred with a simultaneous large increase in trading volumes on both the spot and futures markets for these same products. Commodity markets are also viewed as a barometer of equity market stress, thus the inclusion of commodity bid-ask spreads add an extra dimension of liquidity measurement not available in other versions of liquidity measurement.

The final indicator is based on the average of these four terms:

$$\textit{Euro Liquidity Indicator} = \left(\frac{(BAI + RtoV + LP)}{9}\right)(-1) \;+\; \left(\frac{(Commodity\ liquidity)}{9}\right)$$

The standardisation process is based on the period of 1999 until October 2010 to take account of the crisis that has occurred since 2007. The standardisation method consists of subtracting the mean (μ) from each daily observation to attain the demeaned values and then dividing by the standard deviation (μ) to obtain:

$$Standardised\ Data = \sum_{i}^{N=9} \frac{(Indicator) + \mu_{i(1999-2010)}}{\sigma_{i(1999-2010)}}$$

To test the informational benefits of the indicator, the flow of funds between the individual asset classes used in its preparation must be investigated in-depth. The models selected for this analysis are broken down into individual case studies with different structures added together to improve the explanatory significance of the models. The investigation begins with a correlation investigation between the individual components of the indicator attempting to identify the strong co-movements of investors. The next stage is the Granger Causality tests which attempt to identify the direction of the flows from one market to the next. Based on these flows, we can then use vector autoregression (VAR) techniques to ‘shock’ the markets based on the channels discovered. This is used to test some of the hypothetical events that may occur in the future based on the data available since January 1999. From this analysis, we can test the impact results of the response variables when one other variable in this environment is shocked using impulse response functions. Results and predictions are then inferred from these standard models.

In this chapter, the European liquidity indicator is expressed as an un-weighted average of eight individual components. The individual investment products include equities, commodities, currencies, bonds, options and interest rate markets. The data itself is taken from a combination of Bloomberg and Thompson Reuters DataStream. The data used in the correlation and Granger Causality tests are annual.

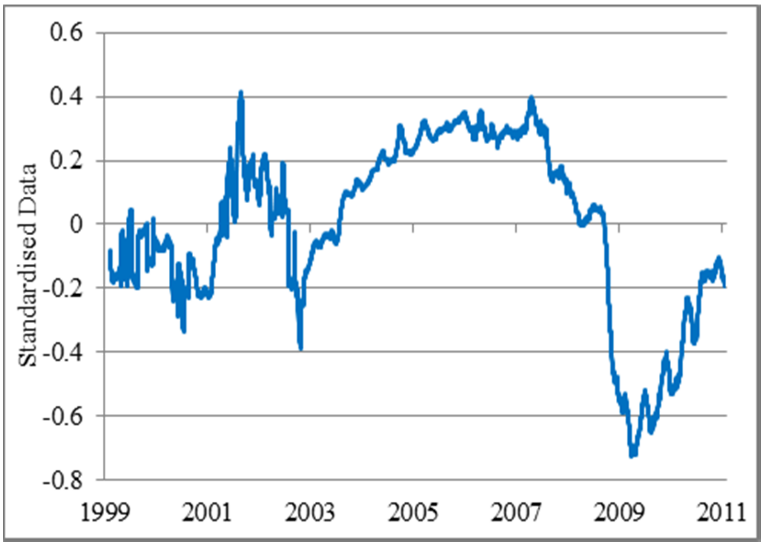
4.4. Results

This section focuses on the aggregation of the individual components to form the final aggregate indicator. It then uses vector autoregression and impulse response functions to test the movements between the financial markets investigated to uncover any significant information. The final section discusses specific benefits that may arise from use of the indicator.

4.4.1. The aggregate European financial market liquidity indicator

The final indicator is an average of these individual components standardised on the 1999-2007 period as discussed in section 4.3. Alternative weighting systems were also investigated, but none outperformed the un-weighted average. The next step was to divide the standardised data by the standard deviation to smooth the results. Some of the datasets were incomplete in the years after the creation of the euro. From 2002 onwards, the indicator is operating with a minimum of six components. Otherwise the indicator is comprised of the total number of components available at that particular point in time. A 30 day moving average was selected as the most adequate window which is indicated by the blue line in figure 4.1.

Figure 4.1: *The European financial market liquidity indicator (1999-2011)*



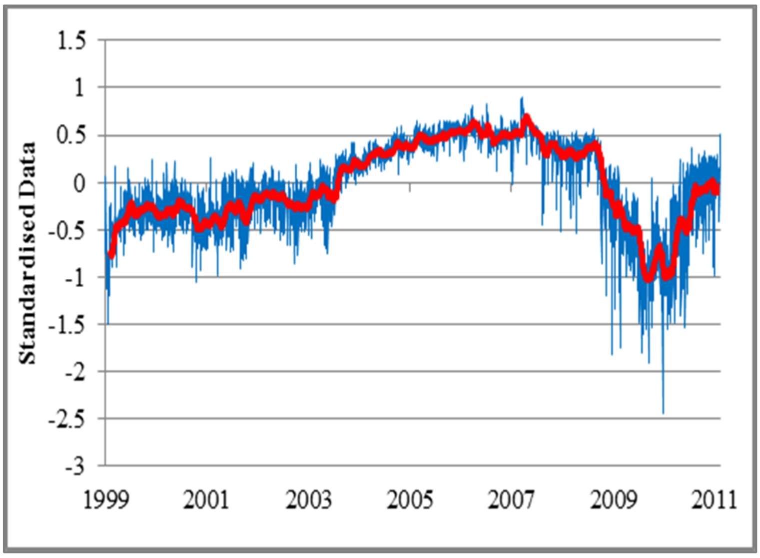
Note: This graph is based on the 30 day moving average of the final liquidity indicator. The early stage between 1999 and 2003 shows extreme volatility based on the evolution of the euro combined with improving market expectations about Europe. From 2007-2009 we can see the depth of the recent crises. Though liquidity as a whole has improved since, this may be due to shorters[74] entering the market to profit from Europe's period of strife.

The individual components of the European liquidity indicator are also shown in figures 4.2 (aggregate bid-ask spread), 4.3 (aggregate return to volume ratio) and 4.4 (aggregate liquidity premia measure). The combination of these three sub-indices results in the aggregate measure

[74] A 'shorter' is a term given to a market agent in possession of a position where he/she gains from a downward movement in the assets price

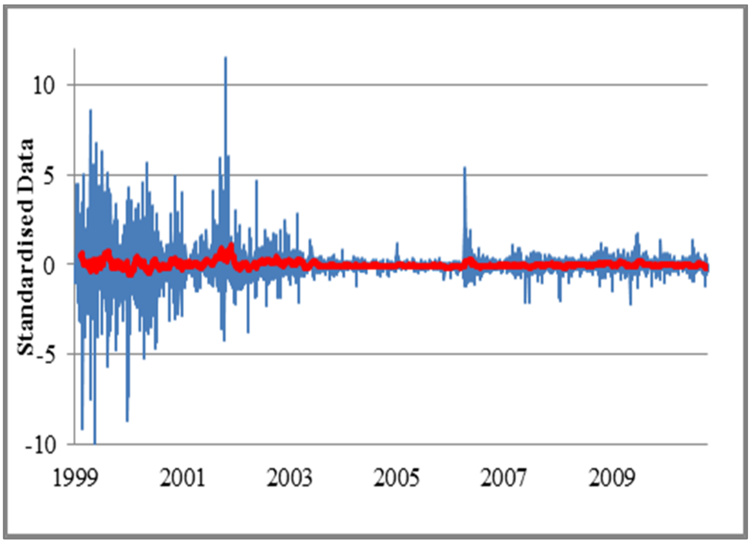
of European financial market liquidity. Some striking trends emerge upon comparison. The first is the development of the bid-ask and return to volume indicators after the introduction of the euro in January 1999. The return to volume measure shows a significant drop in overall volatility. The fall in liquidity premia is slightly unexpected in 1999 but is strongly associated with the evolution of the technology bubble and the events of September 11, 2001 in the United States. Overall, we see an increasing trend in all three measures in the time leading into the current international crisis. The scale of the return to volume measure appears to dominate the measure in the early stages of Eurozone growth, but this stabilises in early 2003. The liquidity premia indicator becomes the most dominant element in the recent crises, stemming from the incredible fall-off in bond and interest markets created by the current uncertainty.

Figure 4.2: *The aggregate bid-ask measure*



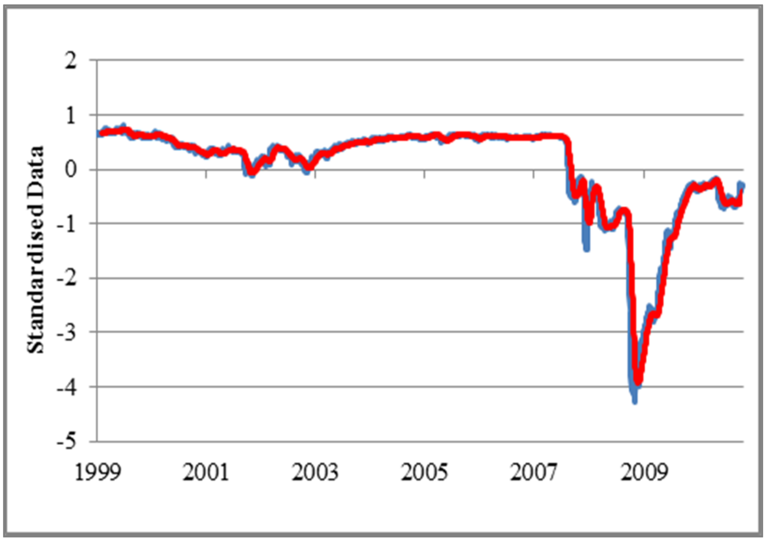
Note: This is a combination of indicators 1, 2 and 3 (defined in table 4.1) and is indicative of the average tightness of the markets investigated. This is the magnitude of the risk premiums required by the market makers for holding inventories of securities. The bid-ask indicator is simply the average of the bid-ask spreads across currency, bond and equity markets. Similarly to the individual markets investigated, there is a clear improvement in liquidity after the establishment of the euro, but this quickly dissipates as market confidence diminishes after the onset of the current financial crisis. Numerous hypotheses have been put forward to explain the increase in greater financial market liquidity and risk taking activity. We can see from figure 4.2, that there were drastic improvements and less volatility in the aggregate bid-ask spread from 2003 to early 2007. But this efficiency collapsed completely until early 2010 where market confidence appears to have slightly improved to early 2004 levels. Investor confidence is directly related to the bid-ask spread. If investors rush en mass to purchase financial market products, the bid-ask spread falls due to increased liquidity.

Figure 4.3: *The aggregate return to volume ratio*



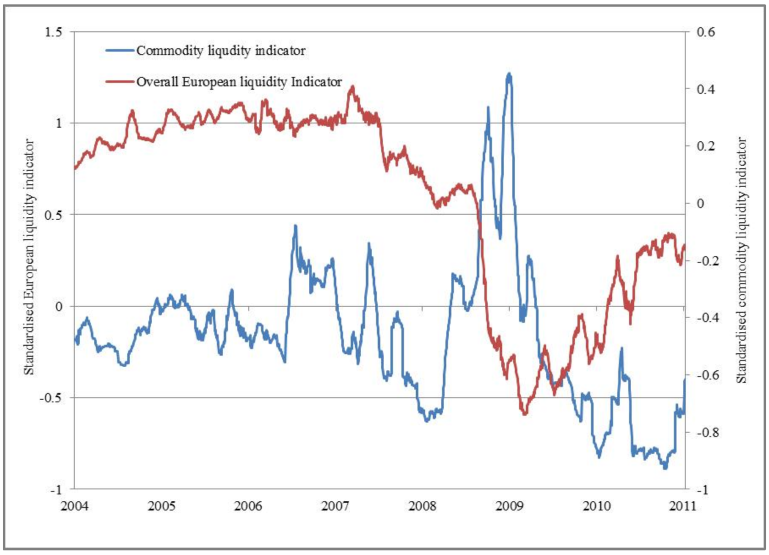
Note: The aggregate return to volume measure is a combination of indicator components 4, 5 and 6 (defined in table 4.1) and is indicative of the average depth and resiliency of the markets included. This is the degree to which trading impacts on asset prices. The aggregate return to volume measures the depth and resiliency of European financial markets as a whole. Unfortunately, the aggregate measure comprises of three individual measures that begin at three different periods since the origination of the euro. The measure does not become an average of all three measures until January 2006. We can clearly see the large dispersion in the results up to early 2003 as the measure is based solely on the equity return to turnover ratio up to this point. One point that the aggregate measure picks up is the increase in the return to turnover ratio from 2007 onwards. This indicates that the prices of components in the measure are reacting substantially to the changes in the volumes traded.

Figure 4.4: *The aggregate liquidity premia measure*



Note: The aggregate liquidity premia measure us a combination of indicator components 7 and 8 (defined in table 4.1) and is indicative of the average liquidity risk premiums required by the markets. This is the compensation required by investors as they attempt to exit their chosen positions which is affected by uncertain market conditions. From figure 4.4, we find the trends with the liquidity premia indicator. Being strongly associated with the normally liquid and efficient interest rate markets, a significant downward shift in liquidity is highly indicative of very high sovereign risk. The depth of the crisis is deemed to be most severe when a liquidity shift such as this occurs in bond markets. It is indicative of the average liquidity risk premiums required by the markets. This is the compensation required by investors as they attempt to exit their chosen positions and it is affected by uncertain market conditions.

Figure 4.5: *The European liquidity indicator compared with commodity market liquidity*



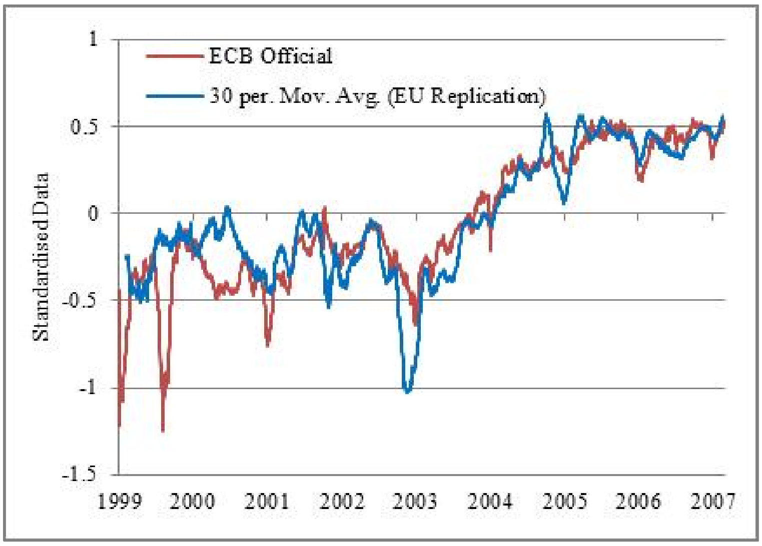
Note: The commodity component of the liquidity indicator was added as a method of controlling for a 'flight to safety'. We can clearly see in figure 4.5 that there is a strong negative correlation between the two metrics. As liquidity collapsed in European markets in early 2007, a simultaneous upsurge in liquidity occurred in commodity markets. Commodity liquidity peaked during the $147 WTI oil price spike of 2008, but fell sharply as gold began to increase substantially in line with large sovereign default threats. As the commodity liquidity element is added to the overall indicator, it acts as a further metric of measuring reduced liquidity in the Eurozone as it increases.

The model in this chapter differs from the indicators of liquidity provided by the European Central Bank and the Bank of England through the inclusion of commodities. If liquidity measurement is based on the main European financial markets, it must also include commodities as a source for investors' funds in periods of international financial stress. The comparison of the European financial market liquidity indicator and the commodity liquidity indicator can be seen in figure 3.5. The inverse relationship suggests that the increased risk in 2007 financial markets shifted liquidity towards commodity markets. Also, in 2008 when oil markets reached their all-time highs, the increased volatility in commodity markets caused risk-averse investors to exit and return to the other products included in the indicator. There appears to have been a reversal of the theoretical 'flight to safety' in this period as commodity markets began to oscillate. Risk-averse investors would have been forced to exit altogether as there was no relatively 'calm' market available during this period.

Comparing the results of the expanded indicator to previous European Central Bank and Bank of England results, we see a similar trend in the period 1999-2007. Initially there was a period of growth as the Eurozone was established. This improvement is clearly visible up to mid-2007. When the financial crisis first developed, stemming from the subprime collapse and instigation of international financial market chaos, we can see a collapse in liquidity in line with market confidence. This was caused by the withdrawal of agents from numerous markets and the increased risk premia sought by market makers. The comparison is seen in figure 4.6.

Overall, after the introduction of the euro, financial markets benefited from the influx of a large number of highly active participants who appear to have had a stabilising influence on market dynamics as the probability of finding market participants in such markets with opposing buy/sell positions became higher. From mid-2007 until late-2009, European markets suffered dramatically from the mass withdrawal of traders, leading to increased volatility in most European markets and increased uncertainty in individual Eurozone nations. Investors began to doubt whether they would be capable of executing transactions involving risky assets without suffering large losses. If the increase in liquidity during the early years of the Eurozone was largely associated with the increased risk appetite of market agents, this same liquidity could disappear quickly based on rational market beliefs such as seen in the collapse in liquidity in mid-2007. The financial market liquidity indicator appears to be a barometer of European market confidence. Some analysts have been sceptical of the depth in the collapse of liquidity.

Figure 4.6: *ECB indicator and this replication compared*

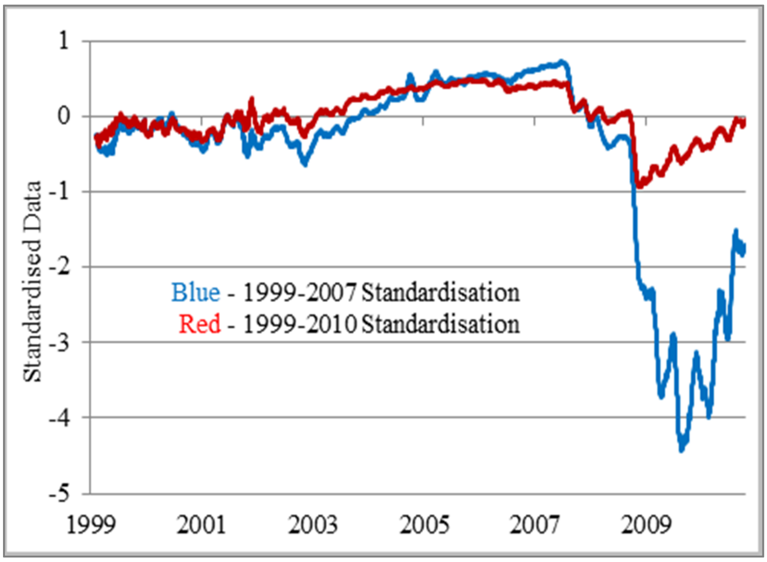


Note: This figure compares the indicator provided in this chapter with the indicator created by the ECB. From this, it can be inferred that there is a strong correlation between the two and any difference may be due to data differentials and differing standardisation process selection. Note that the last replication of the indicator appeared in 2007, thus the 2008-2010 experience is a new finding. The red line indicates the official ECB liquidity indicator, while the blue line indicates the replication developed in this chapter inclusive of commodity liquidity.

One of the major issues associated with the measurement of the liquidity indicator is the period in which the data is standardised. The period 2003-2006 shows the growth of the Eurozone in terms of liquidity. Using both these periods together as the standardisation period leaves an upward trend. Alternatively, using the whole period of 1999-2010 includes the drastic fall-off in liquidity and leaves a downwards trend. The problem with this choice is that none of these standardisation periods are 'normal' thus the choice has a significant impact on the nominal values of the liquidity indicator. In figure 4.7, we can see that the shorter estimate without the most recent crisis included is 'shocked' thus showing an amplification of the crisis in terms of the previous period. Alternatively, including the 2007-

2011 crises, underestimates the growth of the Eurozone after the introduction of the euro, and thus moderates the crisis more effectively.

Figure 4.7: *Depth of the liquidity crises based on the normalisation of the data*



Note: The standardisation process is relevant when estimating the depth of the crisis. We can see that when the crisis is estimated by standardising during a period of normality, the depth increases dramatically. Crises have become more frequent and it may be more efficient to include periods of market chaos in the standardisation procedure.

4.4.2. Where did the recent liquidity crisis originate and how did the liquidity indicator compare with other metrics of financial stress?

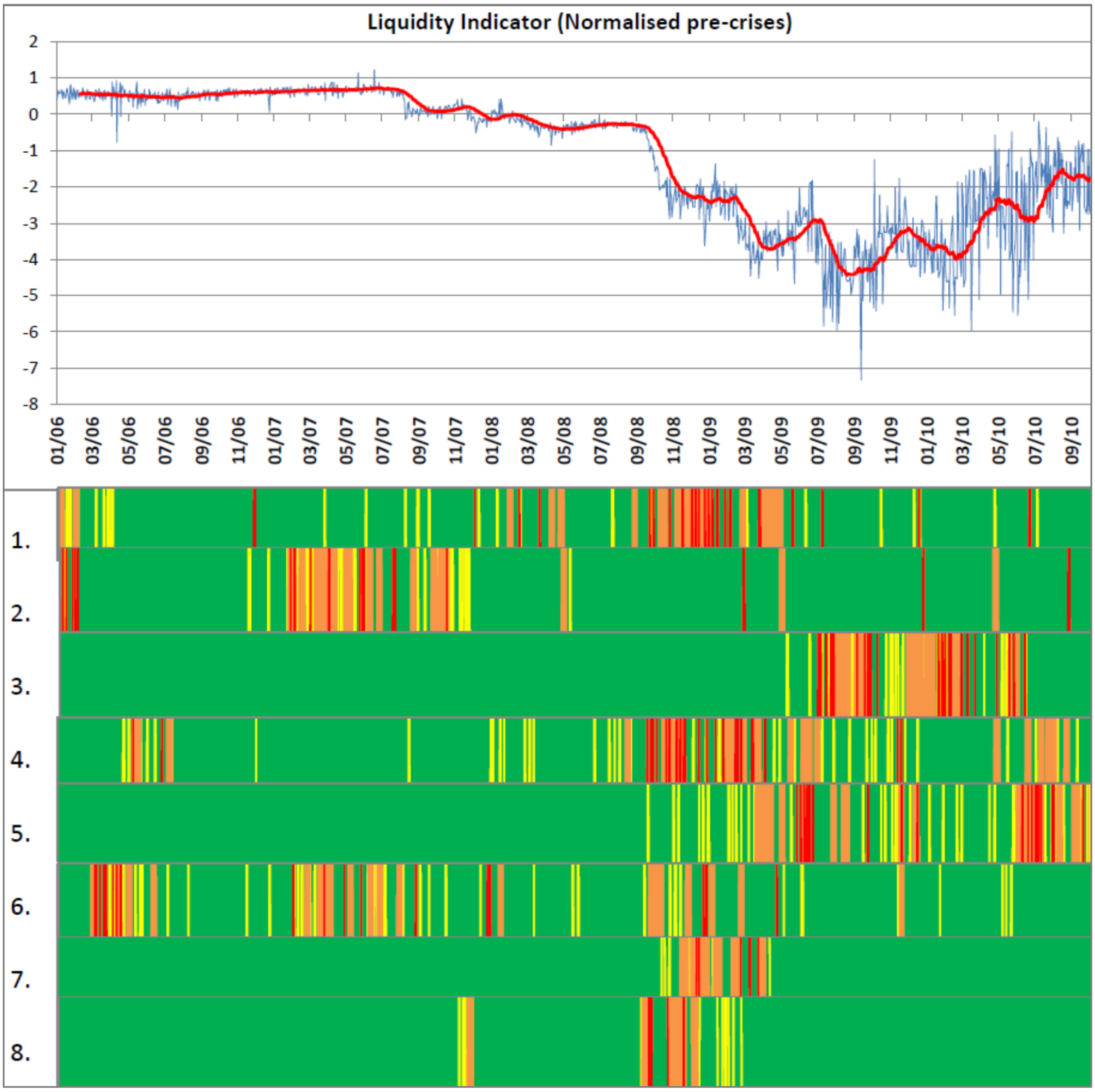
Based on the liquidity indicator developed in section 4.3, it is possible to represent the origins of the episodes of crisis that have occurred since the introduction of the euro in terms of liquidity. Heat-maps are an excellent method of displaying information regarding the flow of funds in the Eurozone. If a warning system regarding liquidity could be established, market makers could impose short term market freezing restrictions based on liquidity rather than volatility. This has been seen in the United States, where large movements in prices have caused markets to close for a set period of time to encourage stability[75]. It is possible to track the flows in and out of the markets in the liquidity indicator in terms of their deviations from normal trends.

A heat-map is a tool used to graphically represent periods of extreme risk using colour codes.Using the combined indicator and a heat-map allows the user to easily view the indicator as a chart and then focus on the heat-map to view the development of a point of interest on the chart directly from the source component. Heat-maps show some interesting

[75] When financial markets move drastically in one day, a forced period of closure occurs to encourage stability. This is known as limit up and limit down. Some markets close trading of these contracts when the limit up is reached; others allow trading to resume if the price moves away from the day's limit. If there is a major event affecting the market's sentiment toward a particular commodity, it may take several trading days before the contract price fully reflects this change. On each trading day, the trading limit will be reached before the market's equilibrium contract price is met. The alternative movement is known as limit down.

facts from where shocks to liquidity in the overall market originated. These are shown in figure 4.8. From the heat-map, the green regions are representative of the 0-80% low nominal value observations, the yellow regions are the 81-87%, the orange regions are the 88-95% range of observations and finally the red regions indicated the highest risk 96-100% of observations.

Figure 4.8: *Heat-map of the European financial market liquidity indicator (Normalised pre-crisis)*

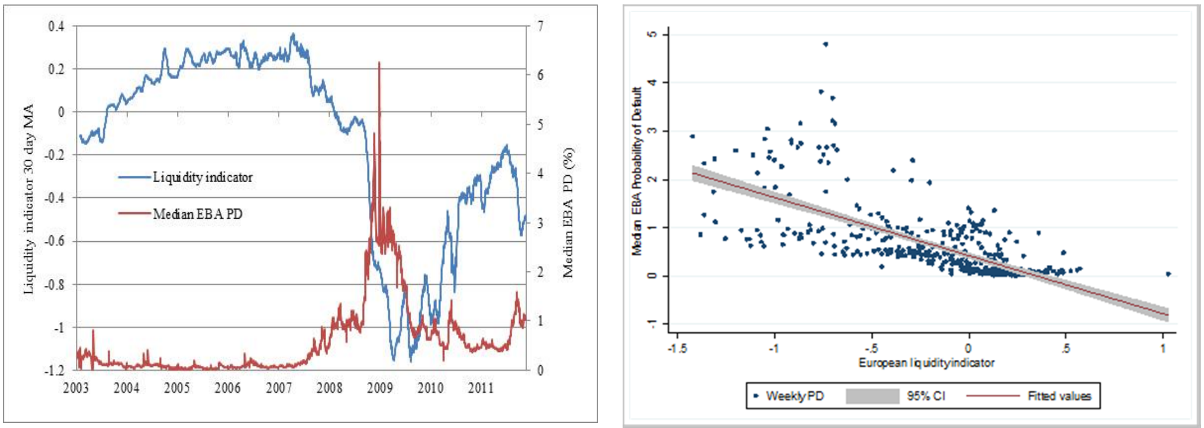


Note: (1) Exchange rate bid-ask spread, (2) Eurostoxx 50 bid-ask spread, (3) EONIA 50 bid-ask spread, (4) Equity market return to volume ratio (5) Euro bond market return to volume ratio, (6) Equity options market return to volume ratio, (7) Spreads on euro high yield bonds, (8) Euro area interest rate spreads. From the heat-maps, the green regions are representative of the 0-80% low nominal value observations, the yellow regions are the 81-87%, the orange regions are the 88-95% range of observations and finally the red regions indicated the highest risk 96-100% of observations.

We can clearly view periods of high volatility prior to the first significant signal of crisis in mid-2007. These periods of volatility stemmed specifically from equity and options markets through bid-ask spreads, return to turnover ratios, whose measures significantly increased. Strong movements in the same markets were the first major signal of the crisis. Interest rate liquidity premia were next to show signs of stress in November 2007 and this was closely followed by strong euro denominated currency volatility until November 2008, with euro bond return to volume ratios reacting at the same time. Interest rate bid-ask spreads were the last component to show signs of crisis in May 2009 which is associated with the freezing of the credit markets that occurred when financial companies became so pessimistic about the long term outlook and futures of other financials, that they saw the associated risk as too high and refused to lend to each other.

It is also of interest to compare the performance of the liquidity indicator with other measures of financial market stress. In Europe some of the main stress metrics include the probability of default (PD) of the main financial institutions. The Kamakura[76] implied PD's offer a measure of the potential for default of a bank within a specified time frame. It stands to reason that market stresses such as the probability of default and contagion effects should affect the market enough to cause liquidity to fall sharply. The relationship between the median EBA[77] (formerly CEBS) bank PD's and liquidity is investigated in figure 4.9 below. There is clearly a strong negative relationship between the two variables, which can be explained by the market fear associated with a sharp increase in the probability of default of a European bank. Though outliers are present, European liquidity is much lower than normal in periods where there is substantial financial risk.

Figure 4.9: *The relationship between European liquidity and EU banking probability of default*

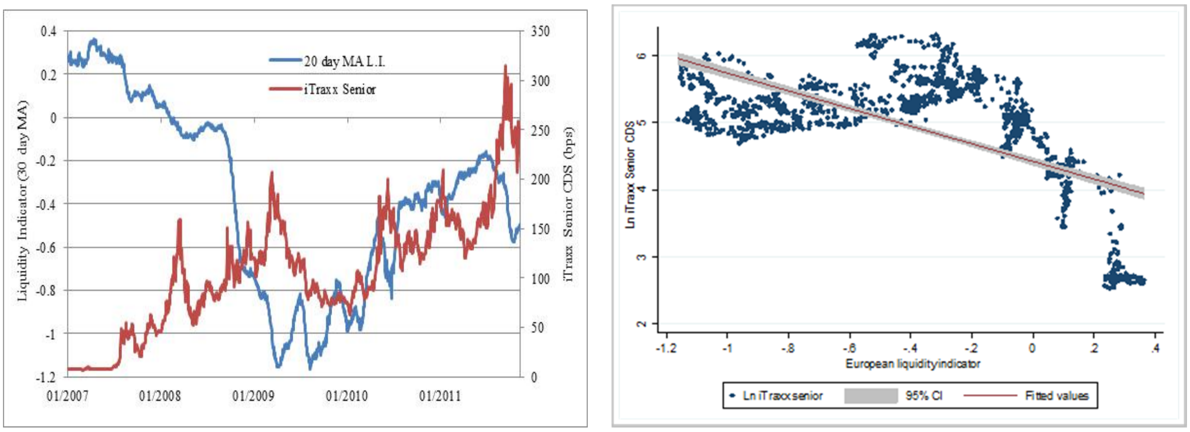


Note: The left-hand figure above shows the relationship between the European liquidity indicator and the median EBA bank 5 year probability of default. A negative correlation is clearly present with periods of dramatic falls in liquidity clearly associated with periods of large increases in potential bank default. The right-hand figure shows a scatterplot of the same variables. The negative relationship can clearly be identified through a linear inclusion, with the tight confidence bands (95%) adding to the clarity of the results.

[76] Kamakura provides default probability measures for public firms, non-public firms and sovereign counterparties which can be used to access credit worthiness of an entire credit portfolio. The models use solid analytical foundation with six yield smoothing methods and five different term structure models for valuation, hedging and pricing of a wide range of products.
[77] European Banking Authority (EBA) chose a panel of banks from which to conduct representative European stress tests. The same tranche of banks is used in this chapter to find the median probability of default of the European banking sector and is compared with the European liquidity indicator in figure 5.5.

There is also significant crisis identification in Credit Default Swap (CDS[78]) prices. The iTraxx Senior CDS indices[79] offer a representation of a weighted basket of senior European CDS prices. The relationship can be seen with the liquidity indicator in figure 4.10 above. There is again a strong negative relationship between the European liquidity indicator and the iTraxx senior European financial CDS which is representative of corporate financials in the Eurozone. The fund is based on the average equally-weighted CDS value which is representative of the demand for insurance against the potential default of one of the companies selected. This is further evidence that panic in this market repels investors, thus they exit. In a scatterplot of the two variables there is again a clear negative correlation. Of particular interest is a potential structural change in the log of the CDS values in periods of high and low liquidity. This is more likely to be explained by the speed and scale by which CDS prices increased. CDS prices of some European banks would have been relatively illiquid, with their basis point spreads not moving for large periods of time. In fact most data sources only have clean CDS data available since January 2007. In mid-2007, the iTraxx index increased substantially from 10bps to 50bps in less than three months. Liquidity would theoretically take longer to react, thus leaving the arced, two-sectional scatterplot evident on the right-hand side of figure 4.10.

Figure 4.10: *The relationship between European liquidity and the iTraxx senior European financial CDS*



Note: The left-hand figure above shows the relationship between the liquidity indicator and the iTraxx senior European financial CDS between January 2007 and November 2011. The iTraxx index is viewed as representative of the average European financial CDS which is based on the market for insurance against the default of the selected 126 financial institutions in the fund. The scatterplot between the two series on the right-hand side shows evidence of a multi-sectional effect which may be caused by the speed at which CDS prices exploded in Europe over the last four years.

Investigating the correlation results and above charts shows that the liquidity indicator in this chapter adequately represented the scale of the recent international crisis in line with other metrics of financial stress used by numerous central banks. The correlation of the indicator is

[78] A Credit Default Swap (CDS) is a product where the buyer of the credit swap receives credit protection, whereas the seller of the swap guarantees the credit worthiness of the product. By doing this, the risk of default is transferred from the holder of the fixed income security to the seller of the swap. For example, the buyer of a credit swap will be entitled to the par value of the bond by the seller of the swap, should the bond default in its coupon payments.

[79] The benchmark Markit iTraxx Senior European indices comprises 125 equally-weighted European financial institutions and trade 3, 5, 7 and 10 year maturities and a new series is determined on the basis of liquidity every six months. It offers information on the perceived risk on the banks in the sample based on the amount of insurance withdrawn to protect from any potential default.

above 0.50 with the main series compared. As the data used in the composition of the indicator is sometimes proxied, the real-time analytical benefits may be deemed inappropriate. It is often with some delay that the alternative metrics of liquidity used in the composition move drastically based on market panic.

4.4.3. Liquidity correlations and Granger causality analysis

The first test based on the liquidity indicator investigates the co-movement of liquidity based on investment product type. This is investigated using correlation tests on a year by year basis between the selected investment channels in this analysis[80]. As some of the individual indicators were unavailable prior to 2002, this investigation is based solely on the recent period of crisis from January 2006 to December 2010. From these results, we will be able to decompose what investment channels were subjected to the largest mass movements of liquidity.

The results for the correlations between products are found in table 4.2 below. From here we can see the co-movement of liquidity into the paired investment products, which provides some interesting results in the lead-up to the crisis. The correlation statistics provide evidence supporting a risk loving appetite of the European market. In periods prior to the increase in commodity and equity volatility, we see an increase in the correlation of liquidity between all assets in the indicator and commodities, indicative of a combined movement towards commodities which is also called a 'flight to safety'. But when the volatility of these products calmed in comparison to the other markets included, there is a negative relationship in the same correlations indicative of contra-flows between these markets. This would indicate that investors believed that markets had calmed either before or during the event and were therefore seeking opportunities in other investment products.

Table 4.2: *Correlations between investment products during the crisis (Jan 2006 - Dec2010)*

Product 1	Product 2	2006	2007	2008	2009	2010	Total
Equities	Currencies	0.0421	0.0702	0.1042	-0.0406	0.2501	0.0677
Equities	Options	-0.0203	0.0283	0.0383	-0.0102	-0.1048	-0.0055
Equities	Int. Rates	0.0931	-0.057	0.138	-0.0068	-0.0162	0.0036
Equities	Bonds	0.0171	-0.0935	-0.0325	0.0169	-0.1041	-0.034
Equities	Commodities	0.0586	0.0513	0.13	-0.0212	0.0974	0.0602
Currencies	Options	-0.082	-0.0186	-0.0124	-0.0757	-0.0572	-0.039
Currencies	Int. Rates	-0.0374	-0.0742	0.0325	-0.054	0.0741	-0.0065
Currencies	Bonds	-0.0368	0.037	-0.0193	-0.0091	-0.1096	-0.0236
Currencies	Commodities	0.0282	-0.1778	0.1044	0.1301	0.2493	0.0866
Options	Int. Rates	-0.0588	0.01	-0.1437	0.1412	-0.0315	-0.0121
Options	Bonds	-0.0519	-0.0199	-0.0654	0.0357	-0.06	-0.0273
Options	Commodities	0.0132	0.0201	-0.0991	0.0627	-0.0077	-0.0118
Int. Rates	Bonds	0.0873	-0.0409	-0.0491	0.0333	-0.0417	-0.0144
Int. Rates	Commodities	0.0745	-0.0736	0.1069	-0.036	0.056	0.0338
Bonds	Commodities	0.0665	-0.0735	0.2953	-0.0551	0.0994	0.1283

Note: The above table shows the correlation between the investigated investment brackets by year from 2006-2010 and also over the total period which is found in the final column.

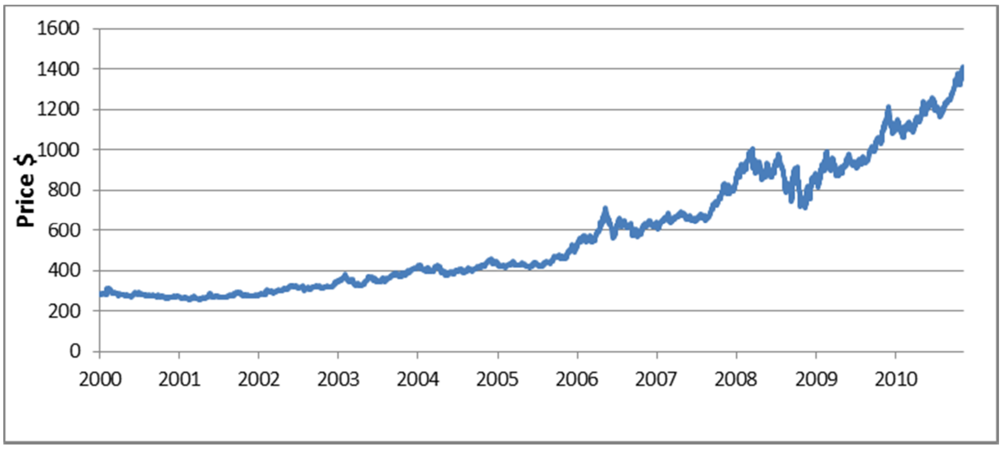
[80] Equities, currencies, options, bonds, interest rates and commodities are the major investment products used in this analysis.

Some particular outliers in correlations deserve individual focus also. These statistics are marked in red in table 4.2. In 2007, there was a negative relationship between currencies and commodities (-0.18). This is indicative of currency hedging based on commodity investment. This is particularly interesting because it occurs in the year before the all-time highs of West Texas Intermediate and Brent Crude oil (figures 4.11 and 4.12 below). Investors were starting to enter these markets 12-18 months before the price spike and were mitigating their US dollar ($) commodity exposure through currency investment. This high correlation continues into 2008, 2009 and 2010. In 2010, this relationship is at its strongest (0.25) and is positive.

Figure 4.11: *West Texas Intermediate price (per barrel)*

Note: The price of oil has also shown dramatic volatility during the period of investigation. The market for West Texas Intermediate oil provides one of the most dramatic spikes seen in market history. Similarly to gold, the subprime crisis did not begin until early 2007, but from 2004 until 2007, the price of WTI more than doubled from below $30 per barrel to over $70. The onset of the crisis in the United States caused dramatic chaos and uncertainty leading to a severe 'flight to safety' to commodity markets.

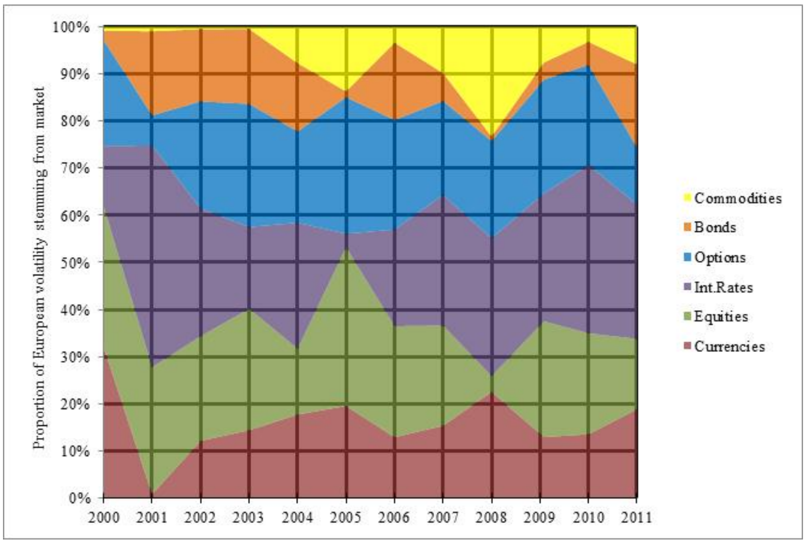
Figure 4.12: *Gold prices (per Troy ounce)*



Note: The price of gold has increased dramatically in recent years. Since late 2004, the price of gold has increased from just under $400 per troy ounce to over $1400 (250% increases). Though the subprime crisis did not start to affect markets until 2007 onwards, there was strong upward pressure on the price of gold between mid-2005 and early 2007, where the price of gold increased from $400 to $700.

As the price of oil started to fall in 2009 and 2010, currency values also changed direction, but the market appears to have been net short[81], leaving the market makers net long and indicating a reversal in hedging tactics from those seen in the previous years. Bonds and commodities also had a correlation of 0.3 in 2008 which indicates that investors with more risk-averse tendencies exited the market due to the large increase in volatility during the year. Commodity movements are synchronised with that of sovereign bonds, which were seen as one of the least risky and most stable products throughout 2008. Of particular interest is the fact that products in the lower risk category show negative values indicating that liquidity also flowed out of high risk markets, which supports the movements of risk-averse investors. Thus, higher risk products appear to have net inflows of funds in co-ordination with other products (indicative of risk loving behaviour) while low risk products show the opposite trend (indicative of risk aversion behaviour). Investigating the correlations between investment channels supports the evidence of significant shifts in asset co-movement. These correlations have strengthened which diminishes the hedging practices used by traders. The correlation changes are also explained by the shifting dynamics of investment patterns. As panic spread across numerous international markets, the threat of sovereign default and the spread of contagion in the international banking system became more likely, there is evidence of a large move from the traditionally low risk classes of bonds and commodities. Risk-averse investors appear to have been in such a dilemma, that not only could they not identify markets of 'least' risk, but their best option may have been to withdraw from investment completely for the short term or at least until a period of calm ensued.

Figure 4.13: *The proportion of annual risk provided by each asset class included in the indicator*

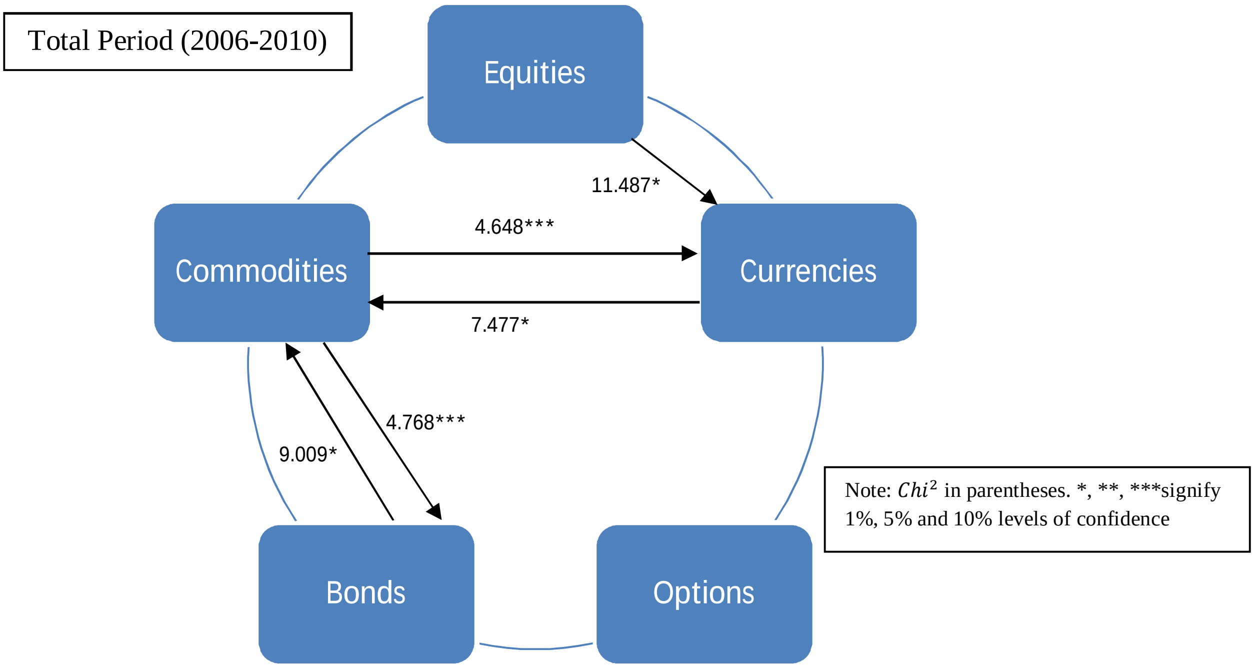


Note: The associated figure shows the proportion of annual volatility associated by year with each of the investment channels in this liquidity indicator. From this we can see the shifting scales of volatility across different assets. Using this data in co-ordination with the flow charts of significant Granger causal movements offers information on the trading environment and reasons to why traders may have entered and exited the same markets.

[81] Net short is indicative of a position that profits more from a downward movement in an asset class than an upward movement.

The next stage of the analysis was to investigate the net flow of funds in terms of Granger Causality as explained in section 4.3. This provides statistical support to the direction of the associated causality, which can then provide evidence whether one investment channel's liquidity move was responsible for the co-movement or counter-movement of another investment product. Figure 4.13 above shows the proportion of annual volatility associated with each asset channel included in the liquidity indicator developed in this chapter. Figure 4.14 shows the flow of liquidity identified by Granger significant relationships over the period investigated from 2006 to 2010. Investigating the main relationships on a year by year basis shows that the main flows that are accepted by the Granger Causality tests are based on the commodity, equity and bond markets. Equities and commodities over the whole period are associated with currency hedging; therefore we see dual flows as investors move in and out of their selected positions. Equities in Europe are associated with currency risk through numerous channels, one of which being the link between the prices of companies such as financials across borders. Similarly, these channels remain open because of the risk preferences of investors. In 2006, it is found that there were significant flows of liquidity from options markets to commodity markets. Given the situation that followed in 2008 in the major commodity markets, this proves to be an interesting finding and may indicate the movement of the typical risk tolerant options trader into the commodity markets.

Figure 4.14: *Flow Chart 2006-2010*



Note: Figure 5.14 visually represents the flow of funds between the investigated investment brackets. Results of the Granger Causality analysis with the associated Chi^2statistic below 10% are marked with an arrow signifying the direction of the move in the period from 2006 until 2010. It is important to note that the above figure does not imply that there was no movement whatsoever between the assets with no Granger significance. Only the connection found with 1, 5 or 10% significance are shown.

In 2007, the main financial developments included the evolution of a commodity price spike and the beginning of the financial crises in equities and bonds. It appears as though a flight to safety occurred during this period which is evident in the flows out of increasingly risky equity and bond markets. Risk adverse investors appear to have left these markets during this time. The year 2008 saw a link from commodities back to bonds, as the same investors may have found the volatility in commodities to be outside the thresholds of what they found acceptable for their portfolios. From figure 4.13 we can clearly see the increase in commodity volatility being associated with oil market price increases and uncertainty. Currency risk became more important due to the high nominal values of commodities, thus this currency risk created a net-outflow of commodity liquidity into currencies. As the commodity market stabilised in 2009, funds began to flow back from bonds as the beginning of the sovereign crises evolved in Europe. Interest rate markets also showed high volatility. Banks stopped lending to each other, thus freezing the credit markets. This finding is supported by interbank lending markets such as TARGET2 in the Eurozone[82] that show clear evidence of a freeze-out in lending.

2010 shows evidence of a very interesting flow change. As commodity markets begin to increase once again, the memory of investors in the market remains extremely cautious about the short-term. As bond risk remains high, speculators appear to be once again entering the commodity markets from options (a channel that opened one year before the lifetime highs of oil), and risk averse investors appear to be exiting commodity markets back into European equities where there may be some value from a potential revival of international financials. The flow from currencies to commodities is also interesting based on strong Euro/US dollar ($) movements in the previous twelve months. The flow of option investors sends a strong signal that those most risk-loving (hence speculative) in nature are focusing strongly on currencies.

4.4.4. Vector Autoregression (VAR) and Impulse Response Functions (IRFs)

This section investigates the specific inter-market linkages found in figure 4.14. The significant relationships are analysed further using vector autoregression, to test for dynamics with other facets of European investment channels. As commodity and equity markets became extremely volatile, risk adverse investors appear to exit their positions in these markets in search of alternative, safer investment assets. There are five significant links based on the Granger causality analysis in section 4.4.3, but only those significant at the 1% level will be further tested by the VAR and IRF analysis. The significant links are:

a) Commodity liquidity shifting to equity markets
b) Currency liquidity shifting to commodity markets
c) Options liquidity shifting to commodity markets

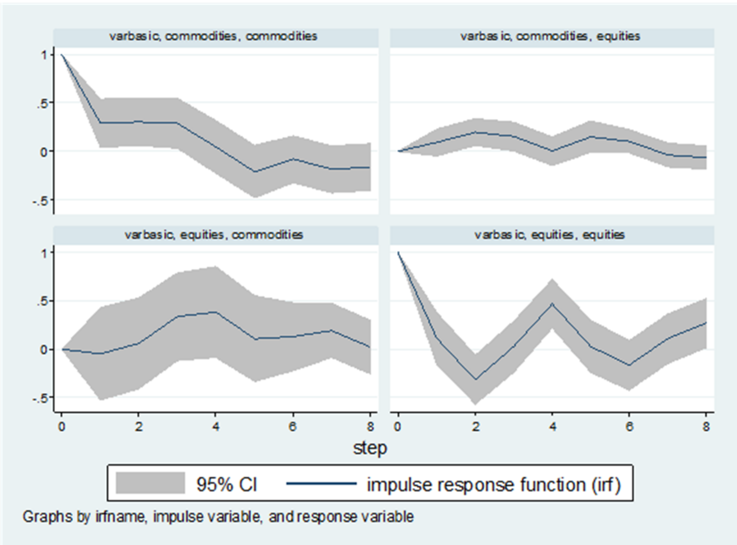
The objective of this analysis is to uncover liquidity movements in the investigated markets. These results are based on the data available in Europe since January 2006. From these three

[82] TARGET2 (Trans-European Automated Real-time Gross Settlement Express Transfer System) is the joint gross clearing system of the ESCB (European System of Central Banks) that unifies the technical infrastructure of the 26 central note-issuing banks of the European Union. It went live on the 19th of November 2007.

linkages listed, we can see that commodity market liquidity shifts appear to have been the most substantial investment channels to which investors flocked during the equity and bond crises since 2007.

First, we look at the relationship between commodity and equity markets. In 2009 and 2010, commodity prices rebounded from the highs of 2008 (figures 4.11 and 4.12). Traditionally, the link between commodities and equities was associated with a 'flight to safety' from volatile equity markets. Based on the results in this chapter, it appears as though equity traders did seek refuge in commodity markets. But in the chaos that followed this mass-shift, some traders invested in a combination of equities, currencies and options. In the non-traditional sense, there was a dual 'flight to safety' based on the risk preferences of the trader. To further analyse the impacts of liquidity movements between these markets, vector autoregression is used. Monthly data were used from January 2006 to December 2010. The summary statistics can be found in tables AVIa to AVIe of the Appendix. The IRF results can be found in figure 4.15.

Figure 4.15: *Impulse response functions* - *relationship between commodity and equity liquidity*



Note: The top right quadrant shows a one unit increase in commodity volatility and its impact on equity volatility. The bottom left shows the impacts of a one unit increase of equity liquidity on commodity liquidity. The top left and bottom right quadrants show the shocks on the variables themselves. The shaded grey area shows the confidence intervals.

The VAR model linking commodities and equities can be written as:

$$Com_t = b_{10} - b_{12}EQ_t + \gamma_{11}Com_{t-1} + \ \ldots . + \gamma_{15}Com_{t-5} + \varepsilon_{Comt}$$

$$EQ_t = b_{20} - b_{21}Com_t + \gamma_{51}EQ_{t-1} + \ \ldots . + \gamma_{55}EQ_{t-5} + \varepsilon_{EQt}$$

The results of the VAR models for the relationship can be found in tables AVIIa to AVIIe of the appendix, along with the associated summary statistics, lag order selection criteria, Lagrange multiplier tests and joint significance tests. From the tables we can see that the lags are strongly jointly significant at the 5% and 10% levels, but when separated, some of the individual lags are not significant. The effects of liquidity increases in one of the variables causes a similar increase in the liquidity of the other variable in both cases, with the effects of commodity liquidity on equity liquidity petering out in two to three months. Equity markets, though possessing large confidence intervals, appear to have little reaction in the first two to five months after the increase in commodity liquidity. There is a theoretical and statistical link still present in European equities and international commodity markets and it appears to have held throughout the recent international crisis, through the traditional commodity to equity channel has been counteracted by a simultaneous equity to commodity market link. The strength of the relationship would be expected to be correlated with the volatility of the markets at a point in time, along with the risk preferences of investors.

The second significant link is based on currency and commodity market liquidity. Currencies and commodities are found to have a strong relationship, given the pricing of major commodity markets in US dollars. Therefore, European investors must monitor their euro to dollar exposures effectively or undertake unnecessary or unwanted currency risk. From the earlier analysis, it appears as the commodity price movements were associated with simultaneous currency investments from Europe (perhaps hedging risk). Granger causality tests for 2010 found a movement from currency markets back into commodity markets. This appears to be associated with de-leveraging and de-hedging strategies as commodity markets calmed, while simultaneous volatility increases occurred in currency markets linked with increased sovereign risk. From the lag order selection criteria, two lags are found to be the optimal specification. The VAR model linking commodities and equities can therefore be written as:

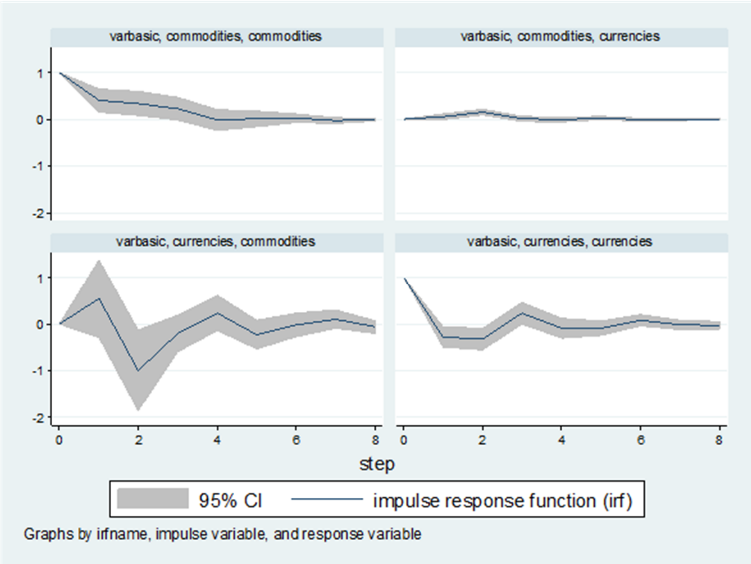
$$Com_t = b_{10} - b_{12}Cur_t + \gamma_{11}Com_{t-1} + \gamma_{12}Com_{t-2} + \varepsilon_{Comt}$$

$$Cur_t = b_{20} - b_{21}Com_t + \gamma_{21}Cur_{t-1} + \gamma_{22}Cur_{t-2} + \varepsilon_{Curt}$$

The impulse response functions are graphically represented in figure 4.16 and the main test statistics of the relationship are found in table AVIIIa in the Appendix.

The results indicate that there was initially a strong negative correlation between commodity and currency liquidity. This is supported by the correlation results which indicate switching directions between the correlations between 2006 and 2010. In 2007 there was negative correlation of -0.18, whereas in 2010 this had switched to 0.25. This change in direction is associated with changing conditions in commodity markets and foreign exchange hedging to mitigate risk. Similarly, with the sovereign debt crisis established in 2009, increased risk in currency markets appears to have deterred investment in safer commodity markets. The volatility of the EUR/USD market also had implications as hedging practices increased based on the strength of each currency and the demand for oil.

Figure 4.16: *Impulse response functions - relationship between Commodity and Currency liquidity*



Note: The top right quadrant shows a one unit increase in commodity volatility and its impact on currency volatility. The bottom left shows the impacts of a one unit increase of currency liquidity on commodity liquidity. The top left and bottom right quadrants show the shocks on the variables themselves. The shaded grey area shows the confidence intervals.

From figure 4.16, we see the impulse response function for the impact of commodities on currency liquidity and vice versa. The Granger causality results indicate that the flow of funds appear to move from currencies to commodities. This is investigated in the bottom-left hand quadrant of the figure above. From this we can see that a one unit increase in currency liquidity leads to over a 0.5 unit increase in the liquidity of commodities. The confidence bands around this estimate are very large, which reduce the benefits of these findings. What is surprising is the drastic decrease in liquidity after one month, with a half unit increase in the first month, being countered by a matching full unit decrease in the second month. This may be associated with reversals of short term hedging strategies, or perhaps even speculators investing in spreads based on the commodity and currency hedging relationship. The influence of commodity liquidity on that of currencies is very mild and shows only a moderate increase up to the second month (0.10) before falling off before the third month. There is still a significant link, but the flow from currency markets to commodities appears to be much more dominant. Given the risk increases in commodity markets, this would give power to the argument that more risk tolerant (hence more speculative) investors may be moving to more volatile markets, hence the migration in recent years from traditionally risky currency markets to increasingly risky commodity markets. Also, non-US traders may have increased currency transactions to hedge dollar related exposure, a risk that would have warranted added attention as commodity prices increased.

The main summary statistics of the relationship between equities and commodities can be found in table AVIIIb in the Appendix. The Lagrange-multiplier test, investigates the relationship for autocorrelation. Evidence of the presence of autocorrelation may indicate that a greater number of lags are needed. The null hypothesis of no autocorrelation is not rejected at the 5% level since the P-value exceeds 0.05.

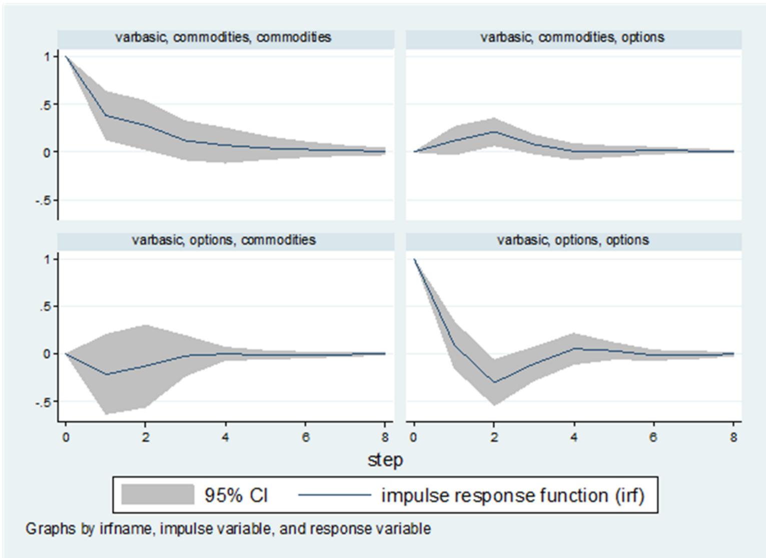
The final significant link is based on the relationship between options and commodity liquidity. Options are traditionally one of the most commonly used speculative investment tools in international markets. Of particular interest is the scenario in 2007, compared to the scenario in 2010. There was a significant link in Granger causality tests from liquidity flowing from options markets to commodity markets. Though the risk expectation of the options markets is significantly higher than commodities markets, the movement of liquidity in this channel is indicative of a mass movement of risk-loving speculators. From the lag order selection criteria, two lags are found to be the optimal specification. The VAR model linking commodities and equities can therefore be written as:

$$Opt_t = b_{10} - b_{12}Cur_t + \gamma_{11}Opt_{t-1} + \gamma_{12}Opt_{t-2} + \varepsilon_{Comt}$$

$$Cur_t = b_{20} - b_{21}Opt_t + \gamma_{21}Cur_{t-1} + \gamma_{22}Cur_{t-2} + \varepsilon_{Curt}$$

The summary statistics representing the relationship between commodities and option is found in tables AVIIIa to AVIIIe of the appendix. The results of this VAR analysis can be found in figure 4.17.

Figure 4.17: *Impulse response functions* **-** *relationship between Commodity and Options liquidity*



Note: The top right quadrant shows a one unit increase in commodity volatility and its impact on options volatility. The bottom left shows the impacts of a one unit increase of options liquidity on commodity liquidity. The top left and bottom right quadrants show the shocks on the variables themselves. The shaded grey area shows the confidence intervals.

In figure 4.17, we see the impulse response function for the VAR tests based on commodities and options. There is significant interest in this link as the same flow of liquidity was present in the year before the commodity price spikes in 2008. In 2010, the same channel has re-opened and is a prime access point for options traders who are traditionally risk loving to enter the ever increasing volatile commodity markets. Granger causality supports this link, but the IRF in the bottom-left quadrant shows a contra-flow between the two markets. Again the extremely large confidence bands reduce the value of these results, but still there is a reduction in commodity liquidity as options liquidity increases.

4.5. Benefits of the European Financial Market Liquidity Indicator

The presence of illiquidity in financial markets acts as a barrier to efficient trading. This arises through the additional cost of purchase (or loss when selling) that arises when a trading partner cannot be quickly found at a price close to that of the current market value. Commodity market liquidity is included as a component in this version of the European Financial Market Liquidity Indicator, aimed at capturing a phenomenon known as the ‘flight to safety’. This component strategically focuses on the effects of international crises on European liquidity, to which commodity liquidity has been found to act as an excellent natural barometer of perceived financial market crises as identified as a phenomenon known as a ‘flight to safety’ where investors have been found to invest in commodity markets in periods of extreme financial stress or panic.

Central Banks and other policy-making institutions can use the liquidity indicator to gauge daily levels of European liquidity. This can be used to monitor large movements of investors’ funds that may be used as a signal of strengthening or weakening crises conditions. Another use for the indicator occurs when there is a shortage of liquidity in a market causing inefficiency. This indicator can act as a gauge, when synchronised with area-specific crisis identifying characteristics, therefore signalling the need for intervention. The indicator can also be used to signal specific movements between different markets, and in particular, which market is acting as the source of any problems. The use of a standardisation period of 1999 to present is also useful, as the selection of a period of normality between 1999 and 2011 has proven difficult due to ongoing crises periods. Other replications assume that financial markets have acted normally between 1999 and 2007, but this simply is not the case. Periods of crises have been ever present and withdrawal of this information may cause the current liquidity crises since 2007 to be overstated. This indicator finds liquidity crises in this period have been present as much as it has not. The use of the longer-term standardisation period also allows for the comparison of crises within this period, offering a more reflective overview of current conditions. In comparison to BOE and ECB replications, this indicator does not appear to overstate particular events and the inclusion of commodity markets allows for the monitoring of one of the largest crises influenced contagion channels available to investors in the form of oil and gold markets.

The addition of commodity liquidity also provides an alternatve channel for European investors, which is found to be regularly used in periods of crises as an alternative market. Other versions of the indicator do not have this channel of liquidity movement, thus cannot show where liquidity has moved. This version of the indicator is shown to be more accurate due to the inclusion of this channel. Regulatory institutions may also find informational benefits from the liquidity indicator to monitor signs of market malpractice.

4.6. Conclusions

Market liquidity is defined as the ease with which an asset can be traded. When there is little in the way of fear or indeed, obstructions to finding counterparties, liquidity is plentiful. The indicator developed in this chapter provides evidence of a strong reaction of liquidity to the major events in Europe and across the world over the last twelve years. The movement of liquidity can act as a barometer of the strength and depth of a particular crisis.

This chapter aimed at developing and adding a new investigative dimension to a liquidity indicator that can be used for macroprudential risk assessment. In comparison to European Credit Default Swaps (CDS) and Probabilities of Default (PDs), the liquidity indicator shows strong analytical benefits. It is however affected by data issues, such as the lack of information available to regulators and investors alike based on the liquidity of bond markets. These data sources are extremely expensive and may easily exceed budgetary allowances for use as only part of this liquidity indicator. There are however proxies available to mitigate these issues, but one hundred percent confidence is unattainable.

The correlations of returns between the channels of investment products in Europe are found to have changed significantly since the emergence of the international crisis. The commodity volatility evident throughout the last decade has changed the structure of investment in products such as equities, currencies and corporate bonds. These investment products have all become highly correlated to what were seen as ‘safe haven’ products such as commodities. A combination of Granger causality, vector autoregression and impulse response functions uncovered strong reactions among particular channels of the liquidity indicator. A large exodus of investment out of equities and into currencies is evident in the period between 2006 and 2010 as investors became sceptical about the health of numerous international financial companies. But the onset of chaos seems to have influenced the results in this chapter that show dual liquidity shifts between bonds and commodities and commodities and currencies.

Much more work must be completed on the inclusion of other assets such as CDS products into the indicator. This current indicator does support use for macroprudential risk assessment in terms of measuring the depth of a crisis and does offer predictive support of oncoming trouble (at the asset class level), but only moderately adds to the predictive power available from other metrics of market stress already available. The heat-maps developed in this chapter in conjunction with this liquidity indicator show that the first signals of international crisis were evident in mid-2006 in the equity options market. Used in conjunction with these other metrics, the liquidity indicator offers information on the health of European markets that is not available through investigation of individual facets of financial market metrics alone.

Concluding remarks

This thesis focuses on three topical issues in international finance, undertaking a thorough investigation of the impact of Contracts for Difference (CFDs) on international equity markets, the impact of Exchange Traded Funds (ETFs) on commodity markets and the measurement of the crisis identification properties available from liquidity analysis in the Eurozone. International finance is an ever-expanding area and the recent subprime and international sovereign debt crises have created an urgency to better understand new investment products and their potential knock-on effects across international markets.

In this thesis, we have examined the effects of CFDs on international equity markets around the world. We have explored whether ETFs really had a role to play in the extreme commodity market environment of the mid to late 2000's. Finally, we have investigated whether there are crisis identification properties available when investigating investor movement across asset-classes in the Eurozone. As the thesis is predominantly an empirical analysis of these areas, we adopt and employ a range of modern time-series econometric techniques that capture the dynamics of volatility, efficiency and liquidity across a range of international financial markets.

Chapter one assesses the primary investigated hypotheses of the thesis in detail. It provides foundations on which the reader can obtain understanding of the investment tools and hypotheses investigated, along with an overview of the numerous channels of investigation available based on the topics investigated.

Chapter two assesses the link between Contracts for Difference (CFDs) and their potential influence on volatility in international equity markets. To investigate this link we utilise GARCH and EGARCH techniques to analyse changes in the structure, volatility and efficiency of these markets in the pre and post-CFD eras. The research provides a number of interesting points. While investigating the special case Australian (ASX) decision to segregate CFDs from the main exchange, a decrease in long-term volatility is uncovered in association with decreased CFD trading. Evaluating each exchange on an equity by equity level shows similar significant results in the case of 90% of those equities investigated. An analysis of major international equity markets echoes this sentiment, while also providing evidence of dramatic improvements in market efficiency. The results suggest that CFDs appear to have helped the markets they have been introduced in. CFDs also appear to have reduced equity market volatility, while simultaneously offering a new tradable product. But these benefits are also found to be associated with the caveat of increased short-term volatility.

Chapter three investigates the potential causal relationship between Exchange Traded Funds (ETFs) and increased volatility present in international commodity markets in recent years. We employ GARCH and EGARCH techniques to test the changes in volatility after ETF introduction and analyse the results in terms of the size of the commodity markets investigated. The main findings in this chapter include significant differences in volatility changes between large and small commodity markets in terms of size. Larger ETF investments are found to be associated with increased EGARCH volatility, thus supporting numerous regulatory views that some ETFs are having dominant effects on the markets in which they invest. This finding supports the need for caps in terms of nominal investment sizes stemming from ETFs. Smaller commodity markets are found to have increased efficiency as measured by weak-form metrics such as persistence and the autoregressive effect. This finding supports the view that liquidity benefits appear to be present in markets below $4 and $5 billion market capitalisation. The findings in this chapter support the calls for more intense regulation of the ETF industry and more investigation into the investment practices and rebalancing processes of the funds investigated.

After investigating the role that CFDs and ETFs are having upon financial markets (as these tools are used for margin trading and shorting financial markets) led this thesis to investigate market liquidity and in particular, what information is contained in European liquidity analysis. Given the large structural changes across financial markets in recent decades and the implementation of new trading tools such as CFDs and ETFs, monitoring the flows of liquidity between assets may offer a substantial amount of information with regards to the depth and magnitude of a crisis along with potential crisis identification benefits.

Chapter four investigates liquidity in European financial markets given the introduction of new investment tools such as CFDs and ETFs. Building on the liquidity model created by the Bank of England and further developed by the European Central Bank through the inclusion of commodities to take account of 'flights to safety' in periods of financial crisis. Using this measure of liquidity, the flows between investment products and the direction of causality can be inferred from Granger causality and vector autoregression (VAR) tests. These variables can also be manipulated using impulse response functions (IRFs) to test the responses of related variables. The mass movements of investors during periods of stability and crisis offer a valuable barometer of market sentiment while potentially offering signals of oncoming crisis. Some of the main findings presented in this chapter are associated with liquidity flows. Market risk thresholds are found to have inverted in recent years with traditionally low risk markets becoming high risk. Correlation and Granger causality tests showed that the flow of funds throughout the recent crisis show that there are strong movements of liquidity flowing into commodity and equity markets. The main channels for liquidity flows are operating as expected, but hedging strategies and speculation in commodity markets appear strong throughout this period. The VAR tests also show strong reactions of the tested variables to liquidity shocks in the markets under observation. There is also strong evidence of market agents exiting particular markets to find 'safer havens' and sheltering from the additional risk that these speculators contribute. Strong correlation results with other metrics of financial market stress offer significant support for the use of the liquidity indicator developed in chapter four for measuring and identifying crisis in the production of macroprudential risk assessments.

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Appendices

Table AI: *EGARCH (1, 1) results for the individual components of the ASX CFD exchange*

Company	β_0	β_1	β_2	β_3	Ω	α	δ	β	Γ	Log-like.
Alumina	0.173	-0.058	1.213*	0.479*	0.149**	0.043	0.293*	0.939*	+0.121**	-1071.061
Amcor	0.174	-0.073***	0.277*	0.387*	0.194***	-0.058	0.025	0.886*	+0.157***	-927.058
AMP	0.036	-0.064***	0.657*	0.319*	0.009	-0.102*	0.149*	1.000*	-0.017**	-1019.106
ANZ	0.082	-0.094**	0.777*	0.255*	0.734*	-0.107**	0.430*	0.463*	+0.919*	-881.6477
AXA	0.171	-0.099*	0.637*	0.533*	3.58*	0.292*	-0.076	-0.712*	+2.447*	-1011.237
BHP Billiton	0.332**	-0.158*	1.007*	0.266*	0.046	0.002	0.217*	0.980*	+0.011	-990.1682
Boral	0.001	-0.026	0.832*	0.319*	0.112**	-0.088*	0.064	0.949*	+0.071**	-1006.355
Coca Cola	0.242**	-0.144*	0.282*	0.07	0.01	-0.051**	0.101*	0.998*	-0.016***	-895.8409
CSR	0.087	-0.165*	1.346*	0.245**	0.006	0.196*	0.094*	1.007*	-0.039*	-1142.148
CBA	0.096	-0.063***	0.524*	0.263*	0.264*	-0.096**	0.294*	0.763*	+0.416**	-832.3569
CSL	0.442**	-0.055	0.248*	0.405*	0.853*	-0.213*	0.04	0.686*	+0.042	-1053.984
Fosters	0.042	-0.129*	0.446*	0.116***	3.066*	-0.092*	0.141**	-0.757*	+0.932*	-894.04
IAG	0.076	-0.032	0.376*	0.451*	3.182*	-0.095**	0.186**	-0.577*	+0.719*	-940.0816
Fairfax	0.012	-0.073**	0.651*	0.244*	3.724*	0.034***	-0.073***	-0.947*	+2.583*	-973.3437

Note: T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10. γ represents the EGARCH calculated volatility change after CFD introduction for the specific Australian equity traded on the ASX CFD exchange.

Table AI: *EGARCH (1, 1) results for the individual components of the ASX CFD exchange (continued)*

Company	β_0	β_1	β_2	β_3	Ω	α	δ	β	Γ	Log-like.
Lihir Gold	0.11	-0.074***	0.878*	-0.026	0.259***	-0.044	0.213*	0.923*	+0.035	-1185.768
Newcrest	0.361***	0.03	0.618*	0.058	0.181	-0.043	0.159*	0.944*	+0.199	-1142.906
News Corp.	0.997*	0.453*	0.065	0.038	3.003*	1.236*	0.856*	0.007	+1.396*	-1147.787
Origin	0.417**	-0.041	0.371*	0.376*	1.097***	0.158**	-0.075	0.493***	+0.487***	-998.9267
Oil Search	0.724*	-0.155*	0.521**	0.848*	3.231*	-0.082	-0.194**	-0.111	+1.223*	-1145.716
Orica	0.191	-0.145*	0.707*	0.407*	1.348*	0.038	0.311*	0.473**	+0.196***	-1027.581
Onesteel	0.23	0.037	0.713*	0.388*	0.152***	-0.018	0.139**	0.94*	+0.056	-1061.864
QBE	0.353**	-0.116*	0.726*	0.094**	3.299*	0.062***	0.052	-0.751*	+2.285*	-963.9783
Qantas	0.009	-0.098*	0.442*	0.45*	4.259*	0.038**	-0.056***	-0.947*	+2.022*	-1001.531
Rio Tinto	0.305***	-0.055	0.752*	0.205*	0.06***	0.017	0.167*	0.981*	+0.018	-1062.44
Santos	0.202	-0.089**	0.619*	0.09*	1.237*	-0.108**	0.347*	0.495*	+0.4**	-1036.621
Suncorp	0.042	-0.11**	0.705*	0.16**	1.422*	0.1***	0.211**	0.204	+1.346*	-963.2643
Tabcorp	0.004	-0.088**	0.911*	0.286*	1.91*	0.179*	0.307*	-0.249	+1.324*	-877.8366
Toll Holdings	0.071	0.012	0.748*	0.297*	3.165*	0.091	1.051*	-0.131**	+0.592*	-1078.936

Note: T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10. γ represents the EGARCH calculated volatility change after CFD introduction for the specific Australian equity traded on the ASX CFD exchange.

Table AI: *EGARCH (1, 1) results for the individual components of the ASX CFD exchange (continued)*

Company	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
Transurban	0.142	-0.096***	0.252*	0.154**	0.193**	-0.007	0.196*	0.893*	+0.183*	-961.4159
Telecom NZ	0.192***	-0.118*	0.62*	0.218*	0.052*	-0.126*	-0.02	0.975*	-0.009***	-919.5852
Westpac	0.062	-0.12*	0.621*	0.176*	0.982*	-0.235*	0.035	0.234	+1.328*	-872.9993
Westfield	0.014	-0.187*	0.436*	0.146**	0.099**	-0.025	0.348*	0.927*	+0.106***	-886.4733
Woolworth	0.225**	-0.162*	0.365*	0.187*	2.864*	-0.045	-0.009	-0.769*	+1.197*	-880.8205
Woodside	0.274***	-0.043	0.826*	0.298*	0.529**	-0.052	0.389*	0.777*	+0.158***	-1018.801
Wesfarmers	0.185*	-0.075***	0.602*	0.277*	0.185*	0.041	0.181*	0.907*	+0.128**	-974.5435

Note: T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10. γ represents the EGARCH calculated volatility change after CFD introduction for the specific Australian equity traded on the ASX CFD exchange.

Table AII: *EGARCH (1, 1) results for the international exchanges under investigation*

Country	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
Dow Jones	0.009	-0.126*	0.334*		0.001	-0.083*	0.140*	0.982*	-0.006*	-6327.740
S&P 500	0.005	-0.134*	0.428*		0.001***	-0.087*	0.129*	0.984*	-0.003***	-6428.531
FTSE 100	0.006	-0.042*	0.534*		0.001	-0.048*	0.151*	0.990*	-0.005**	-5404.856
Germany	0.020**	0.006	0.984*		0.002	-0.033*	0.169*	0.991*	-0.003	-3993.507
Canada	0.021***	0.013	0.622*		0.003***	-0.037*	0.148*	0.991*	-0.001***	-4064.86
Spain	0.004	0.019*	0.449*	0.437*	0.002	-0.015*	0.172*	0.993*	+0.002	-3456.841
China	0.011	0.014	0.068*	0.058*	0.022*	-0.033*	0.150*	0.975*	+0.018*	-5810.724
Japan	0.034**	-0.029**	0.059*	0.358*	0.015*	-0.063*	0.151*	0.980*	-0.008**	-5200.813
Ireland	0.007	0.075*	0.587*	0.117*	0.013*	-0.036*	0.127*	0.987*	-0.006*	-4776.872
South Africa	0.042*	-0.018	0.126*	0.407*	0.013*	-0.056*	0.141*	0.982*	-0.008**	-4888.518
Italy	0.013***	-0.007	0.705*		0.001***	-0.029*	0.235*	0.984*	-0.003**	-3415.462
Thailand	0.048**	0.029**	0.237*	0.341*	0.094*	-0.051*	0.295*	0.922*	-0.012**	-6132.744
Korea	0.065*	-0.003	0.057*	0.637*	0.013*	-0.013**	0.144*	0.994*	-0.009*	-5852.682
Norway	0.034**	0.027**	0.231*	0.514*	0.005**	-0.034*	0.169*	0.978*	+0.009*	-4889.706
New Zealand	0.006	0.079*	0.321*		0.007*	-0.036*	0.108*	0.987*	-0.003**	-3179.332

Note: T-statistics are in parentheses, where ***$p<0.01$, **$p<0.05$ and *$p<0.10$. γ represents the EGARCH calculated volatility change after CFD introduction for the specific international indices under investigation.

Table AIII: *GARCH (1, 1) results for the international exchanges under investigation pre and post CFD introduction*

Country	β_0	β_1	β_2	β_3	α_0	α_1	α_2	Log-like.
Dow Jones Pre	0.045*	-0.062*	0.229*		0.011*	0.927*	0.059*	-3379.141
Dow Jones Post	0.015	-0.147*	0.424*		0.012*	0.879*	0.111*	-2922.186
S&P500 Pre	0.039*	-0.067*	0.339*		0.006*	0.932*	0.062*	-3291.323
S&P500 Post	0.021***	-0.191*	0.548*		0.011*	0.897*	0.094*	-3141.381
FTSE Pre	0.024**	-0.011	0.343*		0.016*	0.900*	0.0692*	-2133.743
FTSE Post	0.002**	-0.027*	0.629*		0.002*	0.921*	0.0790*	-3146.676
TSX Pre	0.019	0.032***	0.571*		0.004*	0.942*	0.056*	-2302.706
TSX Post	0.029***	0.004	0.727*		0.011*	0.895*	0.096*	-1753.512
Spain Pre	0.013	0.016	0.427*	0.405*	0.001**	0.952*	0.047*	-1620.654
Spain Post	0.005	0.029*	0.554*	0.394*	0.005*	0.831*	0.160*	-1062.098
DAX Pre	0.006	-0.024**	1.082*		0.002**	0.948*	0.050*	-2219.850
DAX Post	0.039**	0.019***	0.964*		0.011*	0.857*	0.125*	-976.9168
SSE Pre	0.008	0.031	0.017	0.034*	0.246*	0.695*	0.246*	-2958.668
SSE Post	0.050***	0.005	0.219*	0.126*	0.035*	0.931*	0.060*	-2827.919
NIKKEI Pre	0.016**	-0.031	0.051*	0.239*	0.056*	0.908*	0.062*	-3062.714
NIKKEI Post	0.027	-0.006	0.034*	0.627*	0.019*	0.897*	0.089*	-2040.987

Note: The above table represents the estimated coefficients of the GARCH models based on exchange dynamics prior and post CFD introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIII: *GARCH (1, 1) results for the international exchanges under investigation pre and post CFD introduction (continued)*

Country	β_0	β_1	β_2	β_3	α_0	α_1	α_2	Log-like.
Ireland Pre	0.027	0.137*	0.061*	0.510*	0.110*	0.848*	0.075*	-1924.402
Ireland Post	0.013	0.067*	0.133*	0.692*	0.013*	0.926*	0.065*	-2825.231
South Africa Pre	0.044**	0.119*	0.096*	0.388*	0.007*	0.923*	0.076*	-1895.811
South Africa Post	0.058*	-0.052*	0.129*	0.411*	0.023*	0.905*	0.080*	-3687.66
Italy Pre	0.015	0.004	0.625*		0.003	0.901*	0.092*	-2291.596
Italy Post	0.047*	0.014	0.879*		0.013*	0.806*	0.187*	-1021.029
Thailand Pre	0.011	0.043**	0.205*	0.302*	0.053*	0.898*	0.076*	-3025.875
Thailand Post	0.032	-0.022	0.314*	0.240*	0.087*	0.879*	0.091*	-1311.244
South Korea Pre	0.041	-0.003	0.037***	0.675*	0.0053**	0.964*	0.034*	-2994.880
South Korea Post	0.081*	-0.016	0.075*	0.637*	0.029*	0.839*	0.141*	-1534.367
Norway Pre	0.063*	0.079*	0.408*	0.163*	0.032*	0.887*	0.081*	-1934.824
Norway Post	0.024	-0.003	0.775*	0.322*	0.021*	0.991*	0.079*	-2049.972
New Zealand Pre	0.018	0.037***	0.343*		0.008*	0.909*	0.071*	-1257.481
New Zealand Post	0.002	0.099*	0.291*		0.015*	0.886*	0.081*	-1257.231

Note: The above table represents the estimated coefficients of the GARCH models based on exchange dynamics prior and post CFD introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIV: *EGARCH (1, 1) results for the commodity markets under investigation at ETF introduction*

ETF name	Ticker	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
iShares Silver Trust	SLV	0.046**	-0.079*	-0.020	-0.676*	0.012*	-0.024*	0.112*	0.995*	**+0.001*** **	-5339.1
ETFS Silver Trust	SIVR	0.047**	-0.079*	-0.018	-0.678*	0.012*	-0.024*	0.110*	0.996*	**-0.006** **	-5338.3
Proshares Ultra Silver	AGQ	0.047**	-0.079*	-0.019	-0.677*	0.011*	-0.024*	0.108*	0.997*	**-0.007* **	-5337.4
Powershares DB Silver Fund	DBS	0.047**	-0.079*	-0.021	-0.677*	0.011*	-0.025*	0.111*	0.995*	**+0.004*** **	-5338.5
SPDR Gold Trust	GLD	0.048*	0.010	0.438*	0.991*	0.002***	0.062*	0.089*	0.990*	**+0.003** **	-3672.2
iShares COMEX Gold Trust	IAU	0.047*	0.009	0.044*	0.991*	0.002	0.062*	0.089*	0.989*	**+0.004** **	-3671.9
ETFS Physical Swiss Gold	SGOL	0.052*	0.021	0.062*	1.074*	0.005*	0.057*	0.073*	0.996*	**-0.008* **	-3079.7
Proshares Ultra Gold	UGL	0.052*	0.022	0.062*	1.073*	0.005*	0.058*	0.065*	0.998*	**-0.009* **	-3075.6
Powers DB Gold	DGL	0.048*	0.010	0.044*	0.992*	0.004**	0.063*	0.089*	0.990*	**+0.003** **	-3672.5
Powershares DB Gold Double Long	DGP	0.048*	0.009	0.044*	0.991*	0.003**	0.064*	0.091*	0.989*	**+0.005** **	-3671.9
E-TRACS UBS Bloomberg Gold	UCI	0.050*	0.023	0.063*	1.073*	0.005*	0.054*	0.077*	0.997*	**-0.003** **	-3081.7
Powers DB Gold Short	DGZ	0.048*	0.009	0.044*	0.991*	0.003**	0.064*	0.091*	0.989*	**+0.005** **	-3671.9
iPath Dow Jones – UBS Platinum	PGM	0.102*	0.003	-0.033**	0.545*	0.029*	0.050*	0.239*	0.980*	**+0.021* **	-4795.4

Note: The above table represents the estimated coefficients of the EGARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIV: *EGARCH (1, 1) results for the commodity markets under investigation at ETF introduction (continued)*

ETF name	Ticker	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
E-TRACS UBS Bloomberg Platinum	PTM	0.102*	0.003	-0.033**	0.545*	0.029*	0.051*	0.241*	0.979*	**+0.021***	-4795.5
ETFS Physical Platinum	PPLT	0.109*	-0.005	-0.044**	0.578*	0.023*	0.054*	0.201*	0.992*	**-0.011*****	-3815.6
ETFS Physical Palladium	PALL	0.019	0.055*	-0.152*	1.206*	0.050*	0.018**	0.202*	0.977*	**-0.004*****	-4325.2
United States Oil Fund	USO	0.006	-0.023***	-0.112*	1.167*	0.028*	-0.036*	0.101*	0.988*	**-0.008***	-6317.5
United States Oil Fund (Short)	DNO	0.007	-0.023	-0.116*	1.157*	0.031*	-0.038*	0.099*	0.985*	**-0.020***	-6315.0
United States 12 Month	USL	0.006	-0.023	-0.111*	1.163*	0.022*	-0.034*	0.101*	0.989*	**-0.004**	-6320.9
Powershares DB Oil Fund	SBO	0.009	-0.023	-0.111*	1.166*	0.025*	-0.033*	0.103*	0.989*	**-0.006****	-6319.5
iPath S&P GSCI Crude Oil	OIL	0.008	-0.023***	-0.111*	1.167*	0.026*	-0.035*	0.103*	0.989*	**-0.006***	-6319.2
Powershares Ultra DJ-UBS Crude Oil	UCO	0.003	-0.023***	-0.115*	1.163*	0.018*	-0.034*	0.085*	0.992*	**-0.009***	-6316.7
Powershares DB Crude Oil Double Short	DTO	0.002	-0.023	-0.113*	1.166*	0.021*	-0.034*	0.097*	0.991*	**-0.005****	-6320.3

Note: The above table represents the estimated coefficients of the EGARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIV: *EGARCH (1, 1) results for the commodity markets under investigation at ETF introduction (continued)*

ETF name	Ticker	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
Powershares ultrashort crude oil	SCO	0.003	-0.023	-0.115*	1.163*	0.018*	-0.034*	0.085*	0.992*	-0.010*	-6316.7
RICI Energy ETN	RJN	0.006	-0.023	-0.111*	1.164*	0.022*	-0.033*	0.102*	0.990*	-0.004***	-6320.9
Powershares precious metals	DBP	0.048**	-0.079*	-0.021	-0.678*	0.011*	-0.024*	0.111*	0.995*	+0.004***	-5338.4
iPath Dow Jones	JJC	0.031	-0.041**	-0.234*	0.726*	0.012	-0.002	0.106	0.992*	-0.001	-5170.5
Powershares base metal	DBB	0.000	-0.050*	-0.187*	0.795*	0.817*	0.027*	0.020*	0.936*	+0.937*	-4798.9
Powershares commodity index	DBC	0.001	-0.045*	-0.177*	0.671*	0.008*	0.036*	0.096*	0.972*	+0.024*	-4668.9
iPath Dow Jones	DJP	0.001	-0.046*	-0.178*	0.669*	0.009*	0.034*	0.100*	0.981*	+0.014*	-4673.8
Powershares base metal	DBB	0.004	-0.018	-0.178*	0.600*	0.009*	0.013**	0.091*	0.994*	+0.006**	-5458.3
iPath Dow Jones (gas)	GAZ	0.029***	0.014**	0.017***	0.243**	0.089*	0.035*	0.236*	0.974*	-0.002***	-7688.2
US natural gas	UNG	0.031***	0.014**	0.016***	0.244**	0.092*	0.034*	0.237*	0.973*	-0.005	-7687.9
US 12M natural gas	UNL	0.032	0.015**	0.014***	0.231**	0.094*	0.036*	0.234*	0.973*	-0.024*	-7685.8

Note: The above table represents the estimated coefficients of the EGARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIV: *EGARCH (1, 1) results for the commodity markets under investigation at ETF introduction (continued)*

ETF name	Ticker	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
iPath DJ Coffee	JO	0.068*	-0.021	0.045**	0.073**	0.064*	0.045*	0.159*	0.9648*	-0.048*	-5546.3
iPath DJ Sugar	SGG	0.056	-0.068*	0.143*	0.131***	0.033*	0.021*	0.085*	0.985*	-0.003	-4391.4
iPath DJ Live Cattle	COW	0.033*	0.146*	0.009***	-0.024***	0.014*	-0.023*	0.246*	0.977*	-0.016*	-2821.5
iPath DJ Lean Hogs	COW	0.129**	-0.104*	-0.108*	0.092	0.221*	-0.020*	0.197*	0.935*	+0.012*	-7519.8
RICI Cotton	RJA	0.012***	-0.036**	-0.138*	0.576*	0.018*	-0.007	0.081*	0.989*	+0.002	-5775.7
RICI Wheat	RJA	0.022***	-0.060*	-0.071**	0.647*	0.045*	0.014**	0.126*	0.973*	+0.029*	-6346.9
RICI Corn	RJA	0.042***	0.003	-0.105*	0.482*	0.026*	-0.002	0.119*	0.979*	+0.019*	-5614.4
RICI Soybeans	RJA	0.060**	-0.038**	-0.119*	0.568*	0.010*	0.029*	0.109*	0.996*	+0.002**	-5197.8
iPath DJ Soybeans	JJG	0.060**	-0.038**	-0.119*	0.568*	0.010*	0.029*	0.109*	0.996*	+0.002**	-5197.8
iPath DJ Wheat	JJG	0.017***	-0.061*	-0.066**	0.670*	0.045*	0.014**	0.126*	0.973*	+0.028*	-6347.0
iPath DJ Corn	JJG	0.043***	0.003	-0.105*	0.482*	0.026*	-0.002	0.120*	0.979*	+0.019*	-5614.2
Powershares WTI	DBC	0.006	-0.024***	-0.112*	1.164*	0.028*	-0.036*	0.101*	0.988*	-0.008*	-6317.6
Powershares Brent	DBC	0.019***	-0.028***	-0.075*	1.257*	0.026*	-0.034*	0.082*	0.986*	-0.008*	-6074.0
Powershares Gold	DBC	0.048*	0.010**	0.043*	0.995*	0.001	0.066*	0.100*	0.984*	+0.012*	-3669.1
iPath DJ Corn	DBC	0.032**	-0.008	-0.131*	0.581*	0.034*	-0.011***	0.121*	0.969*	+0.025*	-4679.3

Note: The above table represents the estimated coefficients of the EGARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIV: *EGARCH (1, 1) results for the commodity markets under investigation at ETF introduction (continued)*

ETF name	Ticker	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
Powershares Corn	DBC	0.034**	-0.009	-0.131*	0.582*	0.030*	-0.010	0.118*	0.973*	+0.020*	-4681.5
Powershares Natural Gas	DBC	0.031***	0.014**	0.016***	0.245**	0.091*	0.034*	0.237*	0.974*	-0.005	-7687.8
iPath DJ Natural Gas	DJP	0.117***	-0.006	0.014	0.514*	0.052*	-0.004	0.184*	0.985*	-0.001***	-4753.6
Powershares RBOB	DBE	0.004	0.014**	-0.365*	1.177*	0.040*	0.022**	0.171*	0.987*	-0.005***	-3986.3
Powershares Aluminium	BDG	0.000	-0.050*	-0.187*	0.795*	0.817*	0.027*	0.020*	0.936*	+0.093*	-4798.9
Powershares Brent	DBE	0.022*	-0.028***	-0.075*	1.254*	0.022*	-0.032*	0.085*	0.988*	-0.005**	-6076.7
Powershares WTI	DBE	0.009	-0.023	-0.111*	1.166*	0.025*	-0.033*	0.103*	0.989*	-0.006**	-6319.5
Powershares Index Track	DBC	0.005	0.015**	-0.362*	1.187*	0.043*	0.020**	0.172*	0.987*	-0.007***	-3986.1
Powershares Zinc	BDG	0.004	-0.018	-0.178*	0.600*	0.009*	0.013**	0.091*	0.994*	+0.006**	-5458.3
Powershares Soybean	DBC	0.080*	-0.027	-0.176*	0.636*	0.017*	0.025*	0.134*	0.992*	-0.001***	-4360.9
Powershares Wheat	DBC	0.012***	-0.060*	-0.065**	0.668*	0.034	0.007	0.126*	0.979*	+0.019*	-6348.6
iPath DJ WTI	DJP	0.007	-0.023***	-0.111*	1.168*	0.027*	-0.036*	0.103*	0.988*	-0.007*	-6318.3
iPath DJ Soybeans	DJP	0.060**	-0.038**	-0.119*	0.568*	0.010*	0.029*	0.109*	0.996*	+0.001**	-5197.8
iPath DJ Gold	DJP	0.048*	0.010***	0.043*	0.995*	0.001***	0.066*	0.100*	0.984*	+0.012*	-3669.1

Note: The above table represents the estimated coefficients of the EGARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AIV: *EGARCH (1, 1) results for the commodity markets under investigation at ETF introduction (continued)*

ETF name	Ticker	β_0	β_1	β_2	β_3	ω	α	δ	β	γ	Log-like.
iPath DJ Copper	DJP	0.032	-0.041**	-0.234*	0.728*	0.012*	-0.001	0.106*	0.991*	+0.001	-5170.4
iPath DJ Live Cattle	DJP	0.003*	0.140*	0.008	-0.024***	0.018*	-0.026*	0.243*	0.974*	-0.029*	-2814.0
iPath DJ Wheat	DJP	0.015	-0.061*	-0.071**	0.640*	0.040*	0.008**	0.130*	0.976*	+0.021*	-6349.5
US Gasoline Fund	UGA	0.065	0.031	-0.424*	1.319*	0.011**	-0.008	0.122*	0.997*	+0.003**	-2978.3
Powershares Ag. Live Cattle	DBA	0.022**	0.272*	0.005	-0.026***	0.046*	-0.044*	0.278*	0.929*	-0.033*	-1712.2
PowerS Ag. Coffee	DBA	0.129*	-0.103*	-0.109*	0.091	0.222*	-0.021*	0.197*	0.934*	+0.013*	-7519.1
Powers Ag. Soybeans	DBA	0.060**	-0.038**	-0.119*	0.569*	0.010*	0.029*	0.109*	0.996*	+0.002**	-5197.7
Powershares Ag Corn	DBA	0.041***	0.003	-0.105*	0.483*	0.028*	-0.002*	0.119*	0.975*	+0.021*	-5613.2
PowerS Ag. Wheat	DBA	0.010	-0.062*	-0.066**	0.676*	0.039*	0.010	0.127*	0.977*	+0.022*	-6349.0
PowerS Ag. Cocoa	DBA	0.015	0.020	0.060*	0.162**	0.200***	-0.045*	0.040*	0.709*	+0.137**	-4605.8
PowerS Ag. Lean Hogs	DBA	0.129*	-0.103*	-0.109*	0.091	0.222*	-0.021*	0.197*	0.934*	+0.013*	-7519.1
PowerS Ag. Sugar	DBA	0.054	-0.091*	0.116*	0.116	0.043*	0.012*	0.048*	0.979*	-0.008*	-6271.3
PowerS Ag. Cotton	DBA	0.031	-0.041**	-0.234*	0.727*	0.012*	-0.002	0.106*	0.992*	+0.000	-5170.5
Powershares DB Base Metals Copper	DBA	0.003	-0.023***	-0.115*	1.163*	0.018*	-0.034*	0.085*	0.992*	-0.010*	-6316.7

Note: The above table represents the estimated coefficients of the EGARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AV: *GARCH (1, 1) results for the major international commodity markets under investigation pre and post ETF introduction*

Country	β_0	β_1	β_2	β_3	α_0	α_1	α_2	Log-like.
Silver								
Pre - SLV	0.000	-0.106*	-0.047*	-1.374*	0.000***	0.954*	0.037*	3623.1
Post - SLV	0.000**	-0.041***	0.255*	-2.832*	0.000*	0.876*	0.102*	2974.7
Gold								
Pre – GLD	0.000**	-0.102*	-0.116*	-1.699*	0.000**	0.898*	0.023*	4328.4
Post - GLD	0.000***	-0.086*	0.003	-1.543*	0.000*	0.933*	0.065*	4808.8
Aluminium								
Pre – DBC	0.000	-0.044**	-0.134*	0.681*	0.000*	0.949*	0.031*	4971.3
Post – DBC	0.000**	-0.054**	-0.162*	2.199*	0.000*	0.907*	0.064*	3379.9
Brent Crude								
Pre - DBC	0.001	-0.019	-0.042	0.433**	0.000*	0.899*	0.052*	3700.3
Post – DBC	0.001	-0.001	0.215*	0.617*	0.000**	0.918*	0.070*	2928.8
Coffee								
Pre – DBA	0.000**	-0.046**	-0.061***	-0.201	0.000*	0.789*	0.105*	4463.2
Post – DBA	0.000	-0.147*	-0.001	-0.016	0.000*	0.914*	0.054*	2896.5
Copper								
Pre – BDG	0.000	-0.025	-0.171*	0.833*	0.000*	0.964*	0.033*	6282.6
Post – DBG	0.000***	-0.012	-0.157*	1.532*	0.000*	0.894*	0.085*	3079.3
Corn								
Pre – DBA	0.000	0.065*	0.019	-0.087	0.000*	0.780*	0.141*	4459.5
Post – DBA	0.001***	0.065**	-0.039	0.079	0.000***	0.920*	0.074*	2505.1

Note: The above table represents the estimated coefficients of the GARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AV: *GARCH (1, 1) results for the major international commodity markets under investigation pre and post ETF introduction (continued)*

Country	β_0	β_1	β_2	β_3	α_0	α_1	α_2	Log-like.
Cotton								
Pre – DBA	0.000	-0.114*	-0.012	0.129	0.000*	0.842*	0.142*	4656.6
Post – DBA	0.001***	-0.166*	-0.049	0.141	0.000*	0.813*	0.158*	1057.9
Feeder Cattle								
Pre – DBA	0.000**	-0.015	-0.011	-0.080	0.000*	0.943*	0.053*	6542.8
Post – DBA	0.000	0.009	0.028**	0.014	0.000**	0.950*	0.041*	3528.8
Gasoline RBOB								
Pre – DBC	0.001	0.018	0.050	0.305	0.000*	0.775*	0.115*	1256.4
Post – DBC	0.000	0.046***	0.071	0.170	0.000*	0.920*	0.061*	2751.1
Lean Hogs								
Pre – DBA	0.001*	-0.006	0.006	-0.026	0.000*	0.898*	0.079*	5676.9
Post – DBA	0.000	0.064**	0.055*	-0.043	0.000*	0.841*	0.120*	2983.4
Live Cattle								
Pre – DBA	0.000**	-0.015	-0.011	-0.080	0.000*	0.943*	0.053*	6542.8
Post – DBA	0.000	0.009	0.028**	0.014	0.000**	0.950*	0.041*	3528.8
Natural Gas								
Pre – DJP	0.002*	-0.014	0.042	0.326***	0.000**	0.804*	0.103*	1237.2
Post - DJP	0.000	-0.041***	0.009	-0.091	0.000**	0.923*	0.072*	3403.0
Palladium								
Pre – PALL	0.000***	0.445*	-0.184*	1.726*	0.000*	0.915*	0.079*	6550.1
Post – PALL	0.001	0.062	-0.642*	2.722*	0.000***	0.405***	0.205**	571.6

Note: The above table represents the estimated coefficients of the GARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AV: *GARCH (1, 1) results for the major international commodity markets under investigation pre and post ETF introduction (continued)*

Country	β_0	β_1	β_2	β_3	α_0	α_1	α_2	Log-like.
Soybeans								
Pre – DBA	0.000	-0.040***	0.003	0.061	0.000*	0.948*	0.042*	5099.7
Post – DBA	0.000	0.020	0.044	0.123	0.000*	0.942*	0.050*	2962.4
Sugar								
Pre – DBA	0.000	-0.002	0.076**	0.037	0.000*	0.724	0.186*	4611.4
Post – DBA	0.000	-0.011	-0.020	-0.064	0.000**	0.937*	0.057*	2371.7
Wheat								
Pre – DBA	0.000	-0.002	-0.016	-0.100	0.000*	0.941*	0.034*	4721.7
Post – DBA	0.001	-0.042***	-0.054	0.086	0.000*	0.930*	0.060*	2511.9
West Texas Intermediate								
Pre – USO	0.001	-0.016	-0.044	0.475**	0.000*	0.908*	0.048*	3814.9
Post – USO	0.001	-0.001	0.218*	0.595*	0.000**	0.916*	0.073*	2813.3
Zinc								
Pre – BDG	0.000**	-0.021	-0.136*	0.838*	0.000*	0.969*	0.030*	6129.7
Post – BDG	0.000	0.008***	-0.076**	1.283*	0.000*	0.930*	0.057*	2920

Note: The above table represents the estimated coefficients of the GARCH models based on exchange dynamics prior and post ETF introduction in the respective investigated exchanges. T-statistics are in parentheses, where ***p<0.01, **p<0.05 and *p<0.10.

Table AVIa: *Vector autoregression testing the impact of commodity liquidity on equity liquidity*

Dependent	***Commodities***		***Equities***	
Independents	***Comm/Equities***		***Comm/Equities***	
	Coefficient	**Probability > |z|**	**Coefficient**	**Probability > |z|**
Constant	-0.2881259	0.822	0.9174515	0.199
Commodities				
L1	0.2896138	0.022	0.0911572	0.195
L2	0.2256709	0.090	0.1611211	0.030
L3	0.1390145	0.317	0.868032	0.263
L4	-0.1852711	0.182	-0.0602609	0.437
L5	-0.3739972	0.006	0.0923992	0.220
Equities				
L1	-0.0479434	0.844	0.1093184	0.422
L2	0.800436	0.722	-0.3251877	0.010
L3	0.3038912	0.184	0.0977486	0.444
L4	0.2707822	0.227	0.3161173	0.012
L5	-0.0082398	0.972	-0.1149553	0.376
No. Of Obs.	55			
AIC	14.09164			
HQIC	14.40214			
SBIC	14.89458			
Log Likelihood	-365.5202			
FPE	4567.951			
Optimal No. Of Lags	2030.201			
Variable	**Commodities**	**Equities**		
Parameters	11	11		
RMSE	10.0728	5.62219		
R-square	0.3441	0.4569		
Chi-square	28.8593	46.26258		
Prob>Chi-square	0.0013	0.0000		

Note: The table above shows the Vector Autoregression (VAR) statistics from the analysis completed in section 4.3.1. This analysis was based on the most significant relationships between investment brackets chosen by significant $\mathbf{chi^2}$ statistics under 1% from the Granger Causality analysis. The VAR was completed to test the magnitude of a potential shock to one investment medium on another. With a significant Granger Causality statistic, we can infer that a flow from one medium to another may be linked – whereas the VAR analysis indicates how much of an impact sudden 'shocks' may have on the other.

Table AVIb: *Summary statistics for the VAR analysis testing the impact of commodity liquidity on equity liquidity*

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Commodities	60	0.049558	10.93051	-22.90755	48.41469
Equities	60	0.784596	6.66441	-11.62489	22.97283

Note: The above statistics represent those used in the monthly liquidity analysis. They are representative of the flow of fund in and out of the investigated asset class in question

Table AVIc: *Lag order selection criteria for the vector autoregression (VAR) analysis between commodity liquidity and equity liquidity*

Lag	LL	LR	Df	P	FPE	AIC
0	-386.239				6032.84	14.3807
1	-378.974	14.611	4	0.006	5338.88	14.2583
2	-372.976	11.997	4	0.017	4962.15	14.1843
3	-369.232	7.4867	4	0.112	5018.92	14.1938
4	-363.995	10.475	4	0.033	4810.11	14.1480
5	-359.285	9.4203	4	0.051	***4710.05***	***14.1216***
6	-375.220	4.1296	4	0.389	5099.24	14.1933

Note: The above table represents the selection statistics used to select the number of lags included in the VAR analysis between commodities and equities. LL represents log likelihood, LR is the likelihood ratio, df is the degrees of freedom and p is the probability. The two metrics used to select the number of lags are the FPE (Final prediction error) and AIC (Akaike's Information Criterion) are used. From this, the lowest value represents the optimal lag value; that is the lag order estimate that does not sacrifice the precision of the model for accuracy. In the case between commodities and equities, the model finds this is the 5th lag.

Table AVId: *Lagrange multiplier test for the variables in the VAR analysis between commodity liquidity and equity liquidity*

Lag	Chi^2	Df	Probability > Chi^2
1	4.0655	4	0.39722
2	3.3427	4	0.50220
H_0: $No\ autocorrelation\ at\ lag\ order$			

Note: The Lagrange multiplier test is derived from a constrained maximisation principal. Maximising the log-likelihood subject to the constraint that $\theta = \theta^0$ yields a set of Lagrange multipliers which measure the shadow price of the constraint. If the price is high, the constraint should be rejected as inconsistent with the data. Letting H be the Lagrangian, H = L$(\theta, y) - \lambda(\theta - \theta^0)$, where the first order constraints are $\frac{\delta L}{\delta \theta} = \lambda$; $\theta = \theta^0$, so that $\lambda = s(\theta^0, y)$.

Table AVIe: *Joint significance tests for VAR analysis between commodity liquidity and equity liquidity*

Equation	Commodities			Equities			All		
Lag	Chi^2	Df	Prob>Chi^2	Chi^2	Df	Prob>Chi^2	Chi^2	Df	Prob>Chi^2
1	5.286668	4	0.071	2.410809	4	0.300	7.17304	4	*
2	3.084533	4	0.214	10.84043	4	0.004	13.53607	4	0.009
3	3.324533	4	0.190	2.200094	4	0.333	5.036204	4	*
4	2.692568	4	0.260	6.4543346	4	0.040	8.540142	4	0.074
5	8.04734	4	0.018	1.92476	4	0.382	10.71393	4	0.030

Note: The Wald test is a parametric statistical test named after Abraham Wald with a great variety of uses. Whenever a relationship within or between data items can be expressed as a statistical model with parameters to be estimated from a sample, the Wald test can be used to test the true value of the parameter based on the sample estimate

Table AVIIa: *Vector autoregression testing the impact of currency liquidity on commodity liquidity*

Dependent	***Currency***		***Comm***	
Independents	***Curr/Comm***		***Comm/Curr***	
	Coefficient	**Probability > |z|**	**Coefficient**	**Probability > |z|**
Constant	-0.081039	0.979	-0.0020699	0.999
Currencies				
L1	-0.2784958	0.012	0.5443957	0.202
L2	-0.4266523	0.000	-1.064377	0.015
Commodities				
L1	0.0547578	0.093	0.4074553	0.001
L2	0.1475837	0.000	0.1464679	0.231
No. Of Obs.	58			
AIC	12.15326			
HQIC	12.29164			
SBIC	12.50851			
Log Likelihood	-343.4447			
FPE	650.9079			
Optimal No. Of Lags	460.6703			
Variable	**Currencies**	**Commodities**		
Parameters	5	5		
RMSE	2.46631	9.5476		
R-square	0.3883	0.2973		
Chi-square	36.81003	24.54037		
Prob>Chi-square	0.0000	0.0001		

Note: The table above shows the Vector Autoregression (VAR) statistics from the analysis completed in section 4.3. This analysis was based on the most significant relationships between investment brackets chosen by significant $\boldsymbol{chi^2}$ statistics under 1% from the Granger Causality analysis. The VAR was completed to test the magnitude of a potential shock to one investment medium on another. With a significant Granger Causality statistic, we can infer that a flow from one medium to another may be linked – whereas the VAR analysis indicates how much of an impact sudden 'shocks' may have on the other.

Table AVIIb: *Lag order selection criteria for the vector autoregression (VAR) analysis between commodity liquidity and currency liquidity*

Lag	LL	LR	Df	P	FPE	AIC
0	-386.239				6032.84	14.3807
1	-378.974	14.611	4	0.006	5338.88	14.2583
2	-372.976	11.997	4	0.017	***4962.15***	***14.1843***
3	-369.232	7.4867	4	0.112	5018.92	14.1938

Note: The above table represents the selection statistics used to select the number of lags included in the VAR analysis between commodities and equities. LL represents log likelihood, LR is the likelihood ratio, df is the degrees of freedom and p is the probability. The two metrics used to select the number of lags are the FPE (Final prediction error) and AIC (Akaike's Information Criterion) are used. From this, the lowest value represents the optimal lag value; that is the lag order estimate that does not sacrifice the precision of the model for accuracy. In the case between commodities and currency, the model finds this is the 2nd lag.

Table AVIIc: *Summary statistics for the VAR analysis testing the impact commodity liquidity on equity liquidity*

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Equities	60	0.020663	2.991978	-9.808066	9.34632
Commodities	60	0.049558	10.93051	-22.90755	48.41469

Note: The above statistics represent those used in the monthly liquidity analysis. They are representative of the flow of fund in and out of the investigated asset class in question

Table AVIId: *Lagrange multiplier test for the variables in the VAR analysis between commodity liquidity and currency liquidity*

Lag	Chi^2	Df	Probability > Chi^2
1	0.2383	4	0.99344
2	2.4157	4	0.65979
H_0: $No\ autocorrelation\ at\ lag\ order$			

Note: The Lagrange multiplier test is derived from a constrained maximisation principal. Maximising the log-likelihood subject to the constraint that $\theta = \theta^0$ yields a set of Lagrange multipliers which measure the shadow price of the constraint. If the price is high, the constraint should be rejected as inconsistent with the data. Letting H be the Lagrangian, H = L$(\theta, y) -$ λ$(\theta - \theta^0)$, where the first order constraints are $\frac{\delta L}{\delta \theta}$ = λ; $\theta = \theta^0$, so that λ = s(θ^0, y).

Table AVIIe: *Joint significance tests for VAR analysis between commodity liquidity and currency liquidity*

Equation	Commodities			Currencies			All		
Lag	Chi^2	Df	Prob>Chi^2	Chi^2	Df	Prob>Chi^2	Chi^2	Df	Prob>Chi^2
1	7.674377	2	0.022	14.62548	2	0.001	22.28513	2	0.000
2	30.81868	2	0.000	6.570124	2	0.037	35.81029	2	0.000

Note: The Wald test is a parametric statistical test named after Abraham Wald with a great variety of uses. Whenever a relationship within or between data items can be expressed as a statistical model with parameters to be estimated from a sample, the Wald test can be used to test the true value of the parameter based on the sample estimate

Table AVIIIa: *Vector autoregression testing the impact of options on commodity liquidity*

Dependent	***Options***		***Comm***	
Independents	***Options/Comm***		***Comm/Options***	
	Coefficient	**Probability > |z|**	**Coefficient**	**Probability > |z|**
Constant	0.8540892	0.256	0.1752854	0.892
Options				
L1	0.093876	0.450	-0.2135971	0.315
L2	-0.2847872	0.018	-0.272463	0.895
Commodities				
L1	0.1166248	0.122	0.3797617	0.003
L2	0.153779	0.049	0.1597123	0.232
No. Of Obs.	58			
AIC	14.03749			
HQIC	14.17586			
SBIC	14.39274			
Log Likelihood	-397.0871			
FPE	4283.779			
Optimal No. Of Lags	3031.780			
Variable	**Options**	**Commodities**		
Parameters	5	5		
RMSE	5.94390	10.17960		
R-square	0.2202	0.2012		
Chi-square	16.38065	14.60994		
Prob>Chi-square	0.0025	0.0056		

Note: The table above shows the Vector Autoregression (VAR) statistics from the analysis completed in section 4.3.3. This analysis was based on the most significant relationships between investment brackets chosen by significant chi^2 statistics under 1% from the Granger Causality analysis. The VAR was completed to test the magnitude of a potential shock to one investment medium on another. With a significant Granger Causality statistic, we can infer that a flow from one medium to another may be linked – whereas the VAR analysis indicates how much of an impact sudden 'shocks' may have on the other.

Table AVIIb: *Summary statistics for the VAR analysis testing the impact commodity liquidity on equity liquidity*

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Commodities	60	0.49558	10.93051	-22.90755	48.41469
Options	60	0.6169003	6.417474	-11.6939	17.52119

Note: The above statistics represent those used in the monthly liquidity analysis. They are representative of the flow of fund in and out of the investigated asset class in question

Table AVIIIc: *Lag order selection criteria for the vector autoregression (VAR) analysis between commodity liquidity and option liquidity*

Lag	LL	LR	Df	P	FPE	AIC
0	-386.239				6032.84	14.3807
1	-378.974	14.611	4	0.006	5338.88	14.2583
2	-372.976	11.997	4	0.017	***4962.15***	***14.1843***
3	-369.232	7.4867	4	0.112	5018.92	14.1938

Note: The above table represents the selection statistics used to select the number of lags included in the VAR analysis between commodities and equities. LL represents log likelihood, LR is the likelihood ratio, df is the degrees of freedom and p is the probability. The two metrics used to select the number of lags are the FPE (Final prediction error) and AIC (Akaike's Information Criterion) are used. From this, the lowest value represents the optimal lag value; that is the lag order estimate that does not sacrifice the precision of the model for accuracy. In the case between commodities and options, the model finds this is the 2nd lag.

Table AVIIId: *Lagrange multiplier test for the variables in the VAR analysis between commodity liquidity and option liquidity*

Lag	Chi^2	Df	Probability > Chi^2
1	5.0103	4	0.28624
2	1.7136	4	0.78825
H_0: $No\ autocorrelation\ at\ lag\ order$			

Note: The Lagrange multiplier test is derived from a constrained maximisation principal. Maximising the log-likelihood subject to the constraint that $\theta = \theta^0$ yields a set of Lagrange multipliers which measure the shadow price of the constraint. If the price is high, the constraint should be rejected as inconsistent with the data. Letting H be the Lagrangian, H = $L(\theta, y) - \lambda(\theta - \theta^0)$, where the first order constraints are $\frac{\delta L}{\delta \theta} = \lambda$; $\theta = \theta^0$, so that $\lambda = s(\theta^0, y)$.

Table AVIIIe: *Joint significance tests for VAR analysis between commodity liquidity and option liquidity*

Equation	Commodities			Options			All		
Lag	Chi^2	Df	Prob>Chi^2	Chi^2	Df	Prob>Chi^2	Chi^2	Df	Prob>Chi^2
1	3.330712	2	0.189	9.03792	2	0.011	11.74837	2	0.019
2	8.00772	2	0.018	1.434849	2	0.488	9.126015	2	0.058

Note: The Wald test is a parametric statistical test named after Abraham Wald with a great variety of uses. Whenever a relationship within or between data items can be expressed as a statistical model with parameters to be estimated from a sample, the Wald test can be used to test the true value of the parameter based on the sample estimate