



Analysis of non-synchronous trading effects on the pricing of Exchange Traded Products

An empirical analysis of the effects on ETP price volatility that result when the ETP instrument is listed on an exchange that is in a different time zone to that of the underlying securities basket

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Abstract

Exchange Traded Products (ETPs) have become important members of the investment universe. They are praised by institutional and retail investors alike for their low cost, transparency and efficient pricing mechanisms. ETPs trade much like equity securities but with a unique creation and redemption mechanism which typically aligns quoted prices with the Net Asset Value (NAV) of the underlying securities. This dissertation examines a class of ETPs whose underlying reference basket consists of securities listed on stock exchanges operating in a time zone different to the time zone of the ETP instrument itself, and whose currencies of the underlying securities are different to the currency of the ETP instrument. The ETP instruments reviewed comprise of the iShares MSCI Country Series and are all listed on the New York Stock Exchange (NYSE).

The ETPs are classified into three groups depending on the degree of overlap between the exchange operating times on which their underlying securities are traded and the exchange operating times of the NYSE. These groups are non-synchronous for no overlapping hours, partially synchronous for some overlapping hours and synchronous for overlapping hours.

By assessing a measure of range-based volatility during 15-minute intraday intervals throughout the NYSE trading day, an understanding of the volatility profile of these ETPs is determined and analysed. It is found that non-synchronous ETPs do exhibit a higher relative level of volatility when compared to the partially synchronous group. Within the partially synchronous group, evidence of a regime-shift is observed during the period when the market of the underlying securities transitions from open to closed during the NYSE trading session.

Another factor observed in the relative volatility profile is the impact of foreign exchange translation. ETPs with underlying securities priced in an emerging market currency show higher relative levels of range-based volatility. However, both emerging market and developed market denominated secu-

curities baskets exhibit relatively higher levels of volatility during the opening and closing periods of the US trading day.

The results point to the need for caution and understanding of the underlying reference basket when transacting in these ETPs as investors may inadvertently transact at a price which does not reflect the fair-market value of the underlying securities basket due to price distortions as a result of volatility.

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Chapter 1

1 Introduction

Exchange Traded Products (ETPs) are a rapidly growing segment of the financial instrument universe. Praised for their low cost and efficiency, these passive index trackers are increasingly utilised by institutional and retail investors alike. With financial instrument innovation and the growth in ETP instrument complexity, an increase in scrutiny and research is required. The Flash Crash event on 6 May 2010 (discussed in Section 6.3.2.1) is one incident that demonstrated the potential flaws in the pricing mechanisms of ETPs, albeit for a very short duration.

While ETP prices are not subject to the same supply and demand forces that drive the prices of equity securities, as was observed during the Flash Crash, periods of extreme price volatility are possible. This thesis aims to address some of the concerns associated with ETP volatility by examining the volatility characteristics of ETPs from a select universe listed on the New York Stock Exchange (NYSE). The ETPs examined all have foreign securities which make up their underlying reference baskets.

Using intraday range-based volatility measured in 15-minute intervals through the NYSE trading day, the volatility profile of the select ETP universe is examined. The findings have potential practical implications for market participants transacting in those ETPs with underlying securities baskets listed on markets in differing time zones and with currencies different to that of the ETP instrument itself.

Chapter 3 provides an introduction and overview of ETPs and covers their stock-like transactional ability, transparency and low cost features. Also discussed are ETPs creation and redemption mechanisms and the role of APs play in keeping ETP NAVs in line with ETP prices.

In cases where the underlying securities basket of an ETP is made up of foreign securities, ETPs are not dissimilar in nature to dual or cross-listed securities. Chapter 3 discusses price discovery mechanisms for cross-listed equity securities and ETPs with foreign security underlying baskets.

Chapter 4 introduces volatility which is a critical subject for market practitioners and focusses on range-based volatility as a measure. Also discussed are intraday volatility patterns where systematic variance in trading patterns over the trading day produces distinct volatility shapes.

The prior research of Chapters 2, 3 and 4 is applied to the dataset as described in Chapter 5. In order to understand the distribution profile of the range-based volatility measures, analysis and testing is conducted in Chapter 6. Chapter 7 examines the partially synchronous ETPs in additional detail. The final element of this study is covered in Chapter 8 where the impact of foreign exchange is assessed.

Chapter 2

2 An Overview of Exchange Traded Products

2.1 History of the ETP Industry

Research work and media articles covering the Exchange-Traded Product (ETP) industry typically highlight statistics on the rapid growth of these innovative instruments. There has been a proliferation of products and a gathering of assets under management by ETP providers. The terms Exchange Traded product (ETP) and Exchange Traded Fund (ETF) are used to describe exchange traded investment vehicles. Not all ETPs are funds and ETFs are a subset of the broader ETP universe.

The early building blocks for ETPs came with the implementation of electronic order technology on the New York Stock Exchange (NYSE) and the American Stock Exchange (Amex). Together with the capabilities of large investment banks to execute programme trades, these changes made it possible for investors to pursue futures and stocks arbitrage strategies. Programme or portfolio trades as they became known, attempted to take advantage of pricing discrepancies which arose between the newly created S&P500 futures contracts traded on the Chicago Mercantile Exchange (CME) and the underlying stocks in the S&P 500 index. Settlement of the CME futures, either long or short, could be undertaken in stock, in an exchange of futures for physicals (EFP) (Gastineau, 2001).

Typically, it was large investors making use of EFP trades and smaller institutions and retail investors sought a Securities and Exchange Commission (SEC) regulated product that could deliver the payoff profile of an EFP trade. Index Participation Shares (IPS) mirroring the S&P 500 were introduced and

began trading on Amex and the Philadelphia Stock Exchange in 1989. Unfortunately for investor interests, the CME and the Commodity Futures Trading Commission (CFTC) contested that IPS products were futures contracts rather than stock-like securities. These entities felt IPS products should, therefore, trade on a futures exchange and fall under the regulatory authority of the CFTC. The position of the CME and CFTC was vindicated, and a federal court found IPS products were indeed futures-like in structure. The United States product creators remained unsuccessful in their bid to find a replacement to Index Participation Shares. In Toronto, Canada, Toronto Stock Exchange Index Participations (TIPs) were successfully introduced and listed as stock-like instruments.

The immediately unique feature of the TIPs suite of products was their expense ratio. Script lending was possible, allowing the trustee of the TIPs product to loan out the underlying securities in the basket, passing those revenue streams back to the product investors. Despite the attractiveness to investors who at times experienced a negative expense ratio (they received payment for investing in a TIPs product) it was expensive for the exchange itself. In 2000 the Toronto Stock Exchange (TSE) liquidated the TIPs portfolios. During this time of product advancement in Canada, two new portfolio-as-a-security type instruments were being debuted in the United States.

These two products were Supershares and Standard & Poor's Depository Receipts (SPDRS). The confusing and complex legal structure detracted from the Supershares offering and it was ultimately liquidated. The SPDRS products were the resounding winners in the ETP landscape. Amex, who developed SPDRS, chose to adopt a unit trust structure rather than establishing a costly mutual fund thus paving the way for low-cost instruments. It took time for investors to become comfortable and familiar with the then-novel creation and redemption process, but the asset growth of SPDRS has been exponential.

Another important innovation within the ETP environment came in March 1996 with the establishment of a series of products known as World Equity Benchmark Shares (WEBS). These funds, listed on Amex, tracked various foreign or non-US indices. Foreign stocks made up the underlying hold-

ings basket. Barclays Global Investors (BGI), a subsidiary of Barclays plc, established WEBS. BGI later changed the name WEBS to the more commonly known iShares brand. Aside from being the first to track indices comprised of foreign stocks, BGI took the decision to structure their WEBS offering as a mutual fund rather than a unit trust as SPDRS had done. The flexibility of a mutual fund structure when creating a large number of similar products outweighed the additional establishment costs of the structure.

While iShares and SPDRS were the ETP founding members, as at the end of June 2014, there were 219 ETP providers with 5 359 ETPs and 10 401 listings globally (Fuhr, 2014). The industry has experienced a period of exponential growth and ETPs have established themselves as mainstream products within the institutional and retail investor environment globally.

2.2 Exchange Traded Product Key Features

If the growth in assets under management is a measure of financial product success, then ETPs have undoubtedly been vastly successful. In 2000, ETPs globally comprised assets of US\$79 billion which over the last 14 years have grown to US\$2 640 billion (Fuhr, 2014). To attract such sustained asset flows over the period, there are clearly unique attributes that ETPs possess that have drawn retail and institutional investors alike.

2.2.1 Portfolio as a Stock

The foundations for ETPs came about through the desire to trade a reference basket or portfolio in a single transaction. Initially, the ability to take advantage of arbitrage opportunities between the futures and underlying physical basket created demand for ETPs. Increasingly though, the “portfolio as a stock” concept allowed small retail investors and large institutional investors to gain market representation without the high transaction costs and administrative load of attempting to hold each underlying stock in a particular index. While constituents of a major index like the S&P 500 are all relatively liquid, the same is not true of more niche sections of the market. The ease with

which exposure is gained to specific market segments through a single stock-like transaction is very appealing to investors.

2.2.2 Defined Portfolio Constituents

ETPs typically track a reference index as evidenced by the first generation ETPs that tracked headline indices like the S&P 500, NASDAQ and the EuroStoxx 50. Index tracking came about due to the exemptive relief from various provisions of the Investment Company Act of 1940 granted by the SEC in 1993 to allow ETPs to track designated indices (Investment Company Institute, 2014). Investors, therefore, have a relatively good appreciation of the underlying constituents and the likely payoff profile of these products.

Mutual fund management is typically performed on a discretionary basis. Investors may have a reasonable idea of the likely mutual fund portfolio holdings based on the categorisation and mandate of the mutual fund, however, managers seek to add value by allocating away from a benchmark or index. Thus, investors do not enjoy the same level of certainty on the mutual fund constituents, likely performance profile and level of exposure to a particular segment that they have with ETPs.

Current ETPs have become far more sophisticated in their offering, thanks to further exemptive relief granted by the SEC in 2008. Over and above tracking typical market capitalisation weighted indices, there can now be an element of discretion to their underlying reference basket or a rules-based trading methodology that switches the underlying instruments dependent on market conditions. These “enhanced” indices have developed as investor appetite for new products has grown. ETPs providers have responded, giving investors the ability to gain exposure to derivative type instruments efficiently. These include futures on certain commodities or volatility indices or specialist or illiquid instruments such as emerging market debt or emerging market real estate. The ETP providers have also sought to divide the market into increasingly finer slices providing the ability to have exposure to very niche segments like energy focused master limited partnerships or Japanese healthcare.

New generation ETPs allow investors to have certainty about the underlying constituents in their selected product, but with the ability to access more complex parts of the financial instrument universe that were once the preserve of institutional and hedge fund managers alone.

2.2.3 Creation and Redemption Process

Although ETPs trade through the day in a similar manner to individual equity securities, the creation and redemption process is a key differentiating factor. The mechanics of creation and redemption is discussed in Section 2.3. ETP managers have the ability to absorb the fluctuating demand and supply for their shares without those demand and supply forces impacting the ETP price. Large flows to an open-ended mutual fund can significantly hamper its subsequent performance due to flow-induced trading costs (Guedj & Huang, 2008). ETP performance is not affected by monetary flows.

Following a placement of a large order for a particular ETP, if there are insufficient shares available, the Authorised Participant (AP) can create additional shares to meet the demand. In the case of an equity which typically has a finite number of shares available, a large order or increased demand will drive up the price of the equity security. The converse is true in the case of a redemption order.

2.2.4 Low Cost

As discussed in Section 2.1, the TIPs traded on the Toronto Stock Exchange had periods of not only low, but often negative expense ratios. The TIPs set the scene for one of the distinguishing features of ETPs, namely low cost.

2.2.4.1 Total Expense Ratio

The Total Expense Ratio is a measure of the costs associated with the management and operation of an investment product divided by the assets of the investment product. Expenses typically include management or performance fees, trading costs, administration fees and legal and audit fees.

ETPs tend to have lower management fees and administrative and trading costs than mutual funds. They also don't include any up-front or redemption fees and there is no minimum investment size, unlike the mutual fund industry. A large portion of mutual fund fees are for shareholder accounting services; a net cash flow of a mutual fund through the subscription or redemption of units triggers purchases or sales of the underlying holdings. These transactions require record keeping and validation.

ETP managers also engage in the practice of securities lending. The ETP manager will lend out the securities to a large institution for a period. The borrower of the securities over-collateralises the position typically in cash and the ETP manager earns a return on this collateral. This additional revenue is used to offset some of the ETP expenses benefitting ETP investors.

2.2.4.2 Tax Efficiency

When a mutual fund rebalances its underlying security holdings, the resultant net capital gain is distributed to the investors in the fund on a quarterly basis. When rebalancing occurs within an ETP, there are no immediate tax effects for the investors and investors only realise capital gains when they sell the ETP shares.

The in-kind redemption mechanism of ETPs enables them to meet redemption requests without the need to sell portfolio securities. As a result, redemptions from the ETP will generally not have any tax impact on the non-redeeming shareholders (Rosella & Pugliese, 2006).

2.2.4.3 Spreads

When the shares of an ETP first begin trading on an exchange, the bid-ask spread will typically reflect the average spread of the ETP's underlying holdings (BlackRock Inc, 2013). Over time, this spread tends to narrow substantially, reflecting the liquidity of the ETP itself. Thus, the cost of gaining exposure to the underlying basket of securities is far lower than the average spread or cost of obtaining the securities directly.

2.2.4.4 Trading costs

Long-term investors in mutual funds subsidise trading costs by investors who frequently trade (Hamm, 2010). However, in the case of ETPs, only the investor transacting in the ETP carries the cost.

2.2.5 Intraday Pricing

ETPs trade continuously through the day at prices determined by intraday supply and demand rather than at the calculated net asset value (NAV) (Engle & Sarkar, 2002). When investors wish to participate in a mutual fund, they purchase the fund at an end-of-day NAV – intraday pricing is unavailable. While the closing NAV for ETPs is, like mutual funds, only calculated at the end of the day, throughout the trading day an indicative NAV is provided in 15-second intervals. The intraday NAV is referred to as the iNAV or indicative optimised portfolio value (IOPV).

The ability to trade intraday provides ETPs with a liquidity advantage over mutual funds. Investors can exit or enter a trade at any time during a trading session to capitalise on a perceived transactional opportunity.

2.2.6 Derivatives

As ETPs possess many of the characteristics of equities rather than mutual funds, derivative instruments can be created with the ETP as the underlying asset. This feature allows for the creation ETP derivatives in the form of options and futures. These derivatives enable investors to take leveraged or hedging positions on ETPs. ETPs themselves can also be shorted, enabling investors to construct a payoff profile of their choosing.

2.3 Exchange Traded Product Pricing Mechanisms

As mentioned in Section 2.2.3 ETPs have a unique creation and redemption mechanism that serves to keep ETP prices trading relatively closely to their net asset value. The mechanics of this pricing process involve many in-

dustry participants to ensure the end investor has confidence that the quoted price is a true representation of the value of the underlying basket.

2.3.1 Industry Participants

There are many participants in the ETP production cycle, each fulfilling various functions within the trading and pricing process. ETP managers or sponsors conceptualise the ETP. ETP sponsors are typically large asset managers who elect to provide a non-actively managed or rules-based investment product tracking a particular reference basket. The reference baskets are created by index providers, some are established primary indices tracking various global exchanges while other reference baskets track indices developed specifically for the ETP provider. These bespoke indices allow the ETP provider to offer a wide variety of potential products.

Once an ETP has been conceptualised and obtained appropriate regulatory approval, its shares begin to trade on an exchange.

2.3.1.1 Primary Market Participants

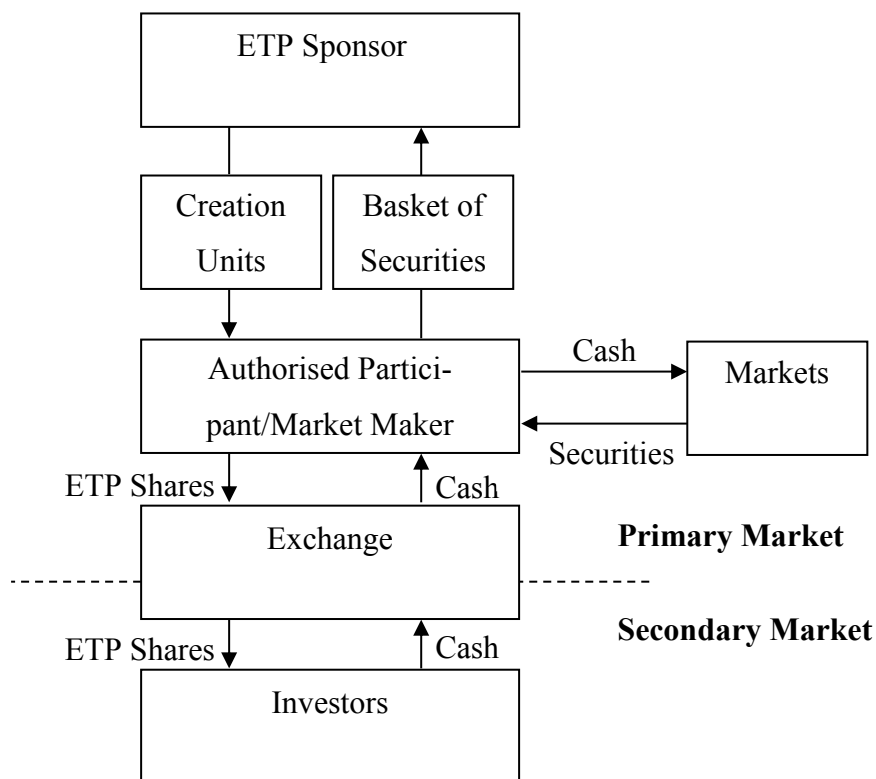
Within the ETP trading process, an Authorised Participant (AP) plays a significant role. The AP is typically a large institutional investor with the ability to settle large share transactions with the ETP sponsor. At the commencement of the trading of a new ETP, the AP will deliver the underlying basket of securities to the ETP sponsor and receive shares of the ETP in exchange. This initial delivery is a primary market transaction undertaken between the AP and the ETP manager; regular institutional and retail investors do not deal directly with the ETP sponsor. While APs are appointed and approved by the ETP sponsor, they do not receive compensation from the ETP sponsor. The costs of purchasing, holding and delivering the underlying reference basket securities are borne exclusively by the AP and the ETP sponsor or regular investors do not incur these costs. APs undertake the role because it generates profit through arbitrage opportunities and provides a useful component to their business. APs continue to deal with the ETP sponsor as the agent to create and redeem ETP shares in the primary market throughout the life of the ETP, meeting secondary market ETP supply and demand requirements.

2.3.1.2 Secondary Market Participants

Regular retail and institutional investors, as well as the AP, will transact in ETP shares in the secondary market. In creating the ability for transactions to occur, institutions fulfil various roles. Within the secondary market, a Market Maker (MM) provides a “two-sided” market. That is, they provide a firm bid and offer price for a listed security, including ETPs. Market Maker is a generalised term, and these market-making institutions do not necessarily have any regulatory or exchange obligations to provide buy and sell prices.

Registered Market Makers (RMMs) are those Market Makers who, as the name implies, are exchange-registered to provide two-sided quotes for particular securities listed on that exchange. Exchanges like NYSE Arca and NASDAQ further differentiate between Registered Market Makers, designating them Lead Market Makers (LMMs) and Designated Liquidity Providers (DLPs), respectively.

Figure 1: Relationship between ETP Participants



2.3.2 Creation and Redemption

ETPs issue and redeem shares in blocks of a minimum size. These blocks are referred to as Creation Units and only the Authorised Participant (AP) can create or redeem them in the primary market. Creation Units typically comprise 25,000 to 50,000 shares or US\$5,000,000. The AP will receive either cash or the basket of underlying securities that make up the ETP from the ETP sponsor. The receipt of physical securities is an “in kind” transaction. The constituents of the “in kind” basket are published at the close of each trading day. APs can buy and sell ETP shares in the secondary market, or transact directly with the ETP sponsor. Although the creation and redemption of shares occurs at the end of the trading day, intraday the AP will sell the more expensive asset (either the ETP shares if the ETP is trading at a premium to NAV or the underlying basket constituents) and buy the cheaper asset. At the end of the trading day, the AP can simply unwind its position by creating or redeeming shares at NAV should it wish to do so. There are of course costs associated with the transfer, and the AP will incorporate those costs into the computation of arbitrage profit prior to embarking on the transaction.

2.3.3 Premiums and Discounts

Premiums and discounts arise when the ETP price is either above or below the ETP NAV. ETPs with illiquid securities in their underlying baskets are more likely to trade at a price different to their NAV. Due to the illiquidity of the underlying securities, APs may find it more difficult and expensive to create the underlying security basket for an in-kind creation or redemption. The arbitrage mechanism is, therefore, less efficient.

Together with the illiquidity of the underlying securities, if the AP has difficulty in determining the NAV of the underlying securities, this introduces an additional element of risk in the arbitrage transaction. International securities traded in different time zones or securities priced in multiple currencies; or indeed in jurisdictions which restrict security ownership all increase the complexity of the NAV calculation.

For non-domestic ETPs, premiums and discounts are observed to be much larger and more persistent. An explanation for this difference may rest with the higher cost of creation and redemption for international products (Engle & Sarkar, 2002). Certain countries will require the payment of taxes during a share transfer process while in other countries there are restrictions on the ownership of securities by foreigners. In these cases, creations and redemptions are cash settled with a domestic trustee holding the securities. The delivery mechanisms are, therefore, slower and more costly (Engle & Sarkar, 2006).

Positive premiums on ETPs lead to more share creation, and vice versa for negative premiums, indicating arbitragers are actively using the ETP share creation and redemption process to trade against these mispricings (Petajisto, 2013). Results using end-of-day data indicate that these premiums are lacking in persistence and vanish over two successive trading days (Rompotis, 2010). The lack of premium persistence confirms that ETPs are efficient investment vehicles for investors with medium to longer-term investment time horizons.

2.3.4 ETP Price Volatility

As ETPs trade on a stock exchange in the same manner as a listed financial security, the price behaviour of the ETP instrument is volatile throughout the trading day. This volatility is due to the prevailing demand and supply for the instrument and information flow creating differing expectations about the potential future price. This price volatility occurs irrespective of the creation and redemption mechanisms that serve to keep the ETP price close to the NAV of the underlying basket and is examined in further detail in Chapter 4.

Chapter 3

3 Dual and Cross-listed Instruments

3.1 Introduction to Dual and Cross-listed Instruments

Dual-listed instruments result in the creation of two separate legal entities that operate as a single business through a legal equalisation agreement. The respective stock-exchange listings of the two entities are typically in two different geographic locations, oftentimes motivated by tax advantages to the shareholders. Additionally, access to diverse capital markets and the associated market regulations can add to the ability of the company to raise capital.

Cross-listed securities comprise of only one distinct legal entity that has issued and listed instruments on a primary and sometimes multiple secondary foreign exchanges. Firms may choose to cross-list to participate in geographically different capital markets in the same way as dual-listed companies.

Cross-listed instruments include American Depositary Receipts (ADRs), European Depositary Receipts (EDRs), International Depositary Receipts (IDRs) and Global Registered Shares (GRSs). A depositary bank purchases the domestic securities and places them with a custodian and issues US Dollar denominated tradeable assets in the form of certificates to create Depositary Receipts which are derivative instruments. The depositary receipts and their domestic underlying securities are not fully fungible; to switch between the two a conversion fee is typically charged. GRSs are a single class of ordinary share listed on both the domestic and foreign exchange. Conversion fees do not apply in switching between the GRS and the domestic stock. As the GRS is denominated in US Dollars when listed on a US exchange and receives dividends in US Dollars rather than the domestic currency, GRSs also not fully fungible.

Surveyed institutional investors reflect that they typically view cross-listed securities as substitutes and make a determination on which instrument to purchase based on liquidity and transaction costs (Moulton & Wei, 2005).

Although ETPs whose underlying baskets comprise of foreign securities not listed on the same exchange as the ETP instrument are not strictly classified as dual or cross-listed, there are definite similarities between the two. To determine the NAV for the ETP, the price of the underlying assets needs to be accurately determined. The mechanics of how the underlying prices of the securities in the reference basket flow through to the ETP during times when the ETP is trading are analogous to the pricing relationship between dual or cross-listed stocks on their respective domestic and foreign exchanges. Importantly, like their ADR counterparts, ETP price discrepancies between the ETP and the underlying basket can be easily arbitrated through in-kind creation and redemption mechanisms.

3.2 Price Discovery

Price discovery is the term given to the determination of the price of an asset through the demand-supply interactions of buyers and sellers. Price discovery is also defined as the search for the equilibrium price and is an important function of an exchange. In the case of dual- and cross-listed securities, prior research has centred on the determination of the flow of information or liquidity between the domestic and foreign exchanges. Previous work largely indicates that for equity securities, price discovery occurs primarily in the domestic or home market of the security.

3.2.1 Equity Security Price Discovery

Chan, Fong, Kho and Stulz (1996) investigated the intraday patterns of European and Japanese dual-listed stocks trading on the NYSE and AMEX. Due to partially overlapping exchange trading hours, public information from European stocks diminishes mid-way through the US trading day as European markets close. The arrival of public information from Japanese stocks is uni-

form and low through the US trading day as Japanese markets are closed throughout the US trading session (Chan, et al., 1996). Following from their analysis, it would appear that US based investors transact in the market on the basis of information accumulated from the previous US market close to the next day's opening. This accumulated information is largest for Japanese stocks that have had a full trading day prior to US open and less for European stocks since there is half a trading day between US market close and open. This notion of reaction to accumulated information provides an explanation for their finding that Japanese and European stocks are most volatile during the US morning trading session.

Eun and Sabherwal (2003) examined a sample of Canadian stocks listed on both the Toronto Stock Exchange (TSE) and the NYSE, Amex or NASDAQ. Their objective was to examine the extent to which the NYSE listed security contributes to the price discovery of the TSE listed security. They suggested that the domestic exchange is likely to contribute meaningfully to the price discovery as material information originates in the home market. However, they also noted that as US exchanges are typically the largest and most liquid globally, they are also likely to contribute to price discovery. As Canadian and US market hours overlap, their findings were potentially different from other work conducted in dual or cross-listed Asian and European securities. They found that the US markets contribute to the price discovery of the Canadian listed securities but for the majority of stocks, the TSE is dominant (Eun & Sabherwal, 2003).

Grammig, Melvin and Schlag (2005) reviewed three German stocks listed on the Frankfurt Exchange (XETRA) and their NYSE listed ADR counterparts. They looked specifically at high-frequency data during overlapping trading hours between the two markets to determine where price discovery occurs. Their empirical results support the assertion that price discovery occurs in the domestic market for the three stocks reviewed rather than the foreign market. A secondary examination was to determine how the security prices reacted to an exchange rate shock. The domestic securities are denominated in Euros while the foreign securities are US Dollar denominated. They found that

the foreign instruments bore almost all the price adjustment to an exchange rate shock – the ADRs re-priced, rather than the domestic stocks. These findings add support to the opinion that price discovery of cross or dual-listed stocks occurs principally in the home market of those stocks (Grammig, et al., 2005).

Agarwal, Liu and Rhee (2007) examined a sample of stocks that trade on both the Hong Kong Exchange (HKEx) and the London Stock Exchange (LSE). The focus of their paper addressed the idea that the foreign market influenced the pricing in the domestic market. This finding would mean that the price information flow is perhaps both from domestic to foreign and from foreign to domestic. They found the setting of LSE opening prices benchmarked against the HKEx close, meaning the LSE market played only a limited role in the price discovery of HKEx stocks. London closing prices were not incorporated into HKEx opening. LSE (foreign) pricing would appear to play an insignificant role in the generation of price information for the HKEx (domestic) pricing (Agarwal, et al., 2007). They suggested that trading of these stocks on the LSE is liquidity-driven rather than information-driven.

3.2.2 ETP Price Discovery

In an examination of price discovery in international iShares Country ETPs listed on the NYSE, Tse and Martinez (2007) reviewed the variance of daytime returns and overnight returns. They suggested that if noise trading or private information drove volatility, then higher volatility would result from increased trading activity. If, however, volatility was due to the flow of information in domestic markets, then the overnight variance would be greater than the daytime variance. They found that the the daytime deviation for both Asian and European ETPs was smaller than overnight deviation with the converse being true for ETPs tracking the American market. Here they found the daytime variance was greater than the overnight variance. They concluded that the volatility of these ETP instruments was driven primarily by public information released during the respective domestic market sessions (Tse & Martinez, 2007).

Hughen and Mathew (2009) reviewed Closed Ended Funds (CEFs) and ETPs trading in the US whose underlying baskets represented non-US securities. Their ETP sample also utilised the international iShares Country ETPs while their CEF universe consisted of those funds classified as world equity and which published a daily NAV. They analysed the transmission of price changes between the value of the underlying security baskets (NAV) and the price of the ETP and CEF instruments listed on US exchanges. They also tested the sensitivity of ETP and CEF prices to the daily returns of the US market. They found that shocks to the NAV of ETP and CEF instruments had a positive effect on prices for several days with the affected period being longer for CEFs than ETPs. They found an overreaction to US stock market returns with both ETPs and CEFs exhibiting a positive relation with the concurrent returns on the S&P 500 (Hughen & Mathew, 2009).

Levy and Lieberman (2013) studied the price formation process of international iShares country ETPs listed on the NYSE. Their findings suggested a changing relationship in the factors contributing to the ETP price. This relationship was dependent on whether the domestic market of the underlying constituents was open or closed during the US trading session. They found that when domestic markets were open, ETP returns were driven predominantly by NAV returns, in other words, the pricing of the underlying securities listed on the home market. However, when the underlying domestic market was closed, they found the returns of the S&P 500 dominated ETP returns. By examining intraday data in 15-minute time intervals throughout the US trading day, they isolated the period when European markets closed during the US morning and examined the principle ETP price drivers before and after this European closing event. They determined that there was a “regime shift” which occurred for European ETPs. The effect of the S&P 500 on European ETP pricing increased significantly after the European market close. They also found that the effect that the S&P 500 returns had on those ETPs whose domestic market was closed throughout the US trading session exceeded the effect it had on the foreign indices which the ETP products track. The ultimate conclusion was an

overreaction to US market returns during non-overlapping trading hours (Levy & Lieberman, 2013).

3.2.3 Comments on Price Discovery

The prior literature focussed on the price discovery of dual or cross-listed equity securities seems to suggest a dominance of the home or domestic market in driving the price behaviour of the security. Equity security research has focussed on intraday periods and covers overlapping and non-overlapping market trading periods. Irrespective of whether liquidity traders or information traders drive price discovery, it seems home markets take the lead in price equilibrium.

In reviewing the literature on ETP price discovery, it should be noted that both Tse and Martinez (2007) and Hughen and Mathew (2009) did not use intraday segmented data. While Tse and Martinez (2007) examined overnight and daytime variance, they did not review periods within the trading day and Hughen and Mathew (2009) focussed on daily returns only. Their conclusions were similar to the general research findings on equity securities the home or domestic market is dominant in driving ETP prices. Levy and Lieberman (2013) did examine ETP data intraday and they found evidence that the dominance of the domestic market varied dependant on whether that domestic market was open during the US trading session or not. The intraday review of European ETPs allowed them to isolate an intraday regime shift and find a dependence on S&P 500 returns as a price driver. This finding is different from the prior work and suggests that further analysis at more granular intraday periods is required to reach a full understanding of the characteristics of ETPs with international underlying securities in their reference basket.

Chapter 4

4 Security Price Volatility

4.1 Introduction to Volatility

From a financial practitioner's perspective, volatility is a critical subject as option and derivative pricing models incorporate a measure of volatility, as do risk and asset pricing models and asset allocation and portfolio construction techniques. Most simply, historical volatility can be computed as the standard deviation of daily returns using close-to-close prices over a particular period. The implicit assumption in this computation is that volatility remains constant over the period which is unrealistic. The calculation of volatility is rendered more complex by the measurement period as data measured over shorter intervals tend to display different characteristics to that measured over longer periods.

Measuring volatility using high-frequency data is the subject of much recent research. Anderson, et al. (2001) propose the usage of a new volatility measure termed "realised volatility". The daily realised volatility is computed by summing the intraday squared returns. Through the use of high-frequency data, the realised volatility computation converges to the underlying volatility. Various researchers have found that in practise, the microstructure noise effects, like a bid-ask bounce begins to distort returns at very high sampling frequencies. This distortion leads to realised volatility computations that are biased and inconsistent (Martens & van Dijk, 2007). The data interval selected needs to incorporate a balance between the desires for almost continuous data i.e. very high frequency and the resulting contamination by microstructure effects (Anderson, et al., 2001).

An alternative to realised volatility computations is to estimate volatility using trading range data, in other words, open-high-low-close data points. Us-

ing additional price range data has been shown to be more efficient than relying on closing prices alone. Martens and van Dijk (2007) assert that the daily range as a volatility measure is more robust against the effects of microstructure noise than realised volatility or variance. They employ a range-based approach to volatility estimation, and their empirical findings confirm that range volatility estimates can compete and improve upon realised volatility at commonly used data frequencies.

4.2 Range-based Volatility

Feller (1951) was the first to propose that the trading range of a financial security followed a geometric Brownian motion pattern. Brownian motion, named after work conducted by botanist Robert Brown, is a continuous, stochastic process that can be used to describe the price evolution of financial assets. Building on this work, Parkinson (1980) proposed a volatility estimator using the high and low prices of securities to determine a range. The drawbacks for the Parkinson estimator of volatility are the assumptions of continuous trading and zero drift. It also does not accommodate overnight jumps in security prices. Below is the Parkinson volatility estimator. (Bennett & Gil, 2012)

Equation 1

$$Volatility_{Parkinson} = \sigma_P = \sqrt{\frac{1}{4\ln(2)} \sum_{i=1}^N \left(\ln \frac{h_i}{l_i} \right)^2}$$

Where:

h_i is the high price of interval i

l_i is the low price of interval i

Garman and Klaas (1980) improved the range-based estimation proposed by Parkinson by including the open and close prices of the security together with the high and low prices. Like Parkinson's solution, the Garman-

Klaas estimator assumes continuous trading, zero drift and does not account for overnight price jumps. Below is the Garmin-Klaas volatility estimator (Bennett & Gil, 2012).

Equation 2

$$\begin{aligned} \text{Volatility}_{\text{Garmin-Klaas}} &= \sigma_{GK} \\ &= \sqrt{\sum_{i=1}^N \frac{1}{2} \left(\text{Ln} \left(\frac{h_i}{l_i} \right) \right)^2 - (2\text{Ln}(2) - 1) \left(\text{Ln} \left(\frac{c_i}{o_i} \right) \right)^2} \end{aligned}$$

Where:

h_i is the high price of interval i

l_i is the low price of interval i

c_i is the close price of interval i

o_i is the open price of interval i

The weaknesses of both the Parkinson estimator and the Garman-Klaas estimator are the assumptions of geometric Brownian motion with no drift and no overnight jumps. Satchell and Rogers (1991), sought to establish an estimator that allowed for drift, in other words, securities that have a non-zero mean, or expected returns that are non-constant. Given real-world security price behaviour, these assumptions are more realistic. Their proposed volatility estimator is presented below (Bennett & Gil, 2012).

Equation 3

$$\text{Volatility}_{\text{Rogers-Satchell}} = \sigma_{RS} = \sqrt{\sum_{i=1}^N \text{Ln} \left(\frac{h_i}{c_i} \right) \text{Ln} \left(\frac{h_i}{o_i} \right) + \text{Ln} \left(\frac{l_i}{c_i} \right) \text{Ln} \left(\frac{l_i}{o_i} \right)}$$

Where:

h_i is the high price of interval i

l_i is the low price of interval i

c_i is the close price of interval i

o_i is the open price of interval i

Yang and Zhang (2000) also sought to address some of the weaknesses in the Garman-Klaas estimator by providing a mechanism for the inclusion of overnight jumps. Bennett and Gil (2012) report that approximately 1/6th of total equity volatility occurs outside of the trading day and is as a result of overnight jumps (Bennett & Gil, 2012). The inclusion of overnight jumps is, therefore, an important component of volatility estimation. The Yang-Zhang-Garman-Klaas extension that includes an ability to incorporate overnight jumps, but still assumes zero drift is given as follows (Bennett & Gil, 2012):

Equation 4

$$Volatility_{GKYZ} = \sigma_{GKYZ}$$

$$= \sqrt{\sum_{i=1}^N \left(\ln \left(\frac{o_i}{c_{i-1}} \right) \right)^2 + \frac{1}{2} \left(\ln \left(\frac{h_i}{l_i} \right) \right)^2 - (2\ln(2) - 1) \left(\ln \left(\frac{c_i}{o_i} \right) \right)^2}$$

Where:

h_i is the high price of interval i

l_i is the low price of interval i

c_i is the close price of interval i

o_i is the open price of interval i

c_{i-1} is the close price of interval i – 1

Yang and Zhang (2000) show those range based estimators that assume no drift in security prices tend to overestimate volatility while those which assume no jumps in opening prices tend to underestimate volatility. They proposed an estimator that could handle both overnight jumps and non-zero drift. The Yang-Zhang estimator is the sum of the estimated overnight variance, the estimated opening market variance and the Rogers-Satchell drift independent estimator (Chou, et al., 2009). The estimator is provided below (Bennett & Gil, 2012).

Equation 5

$$\begin{aligned} \text{Volatility}_{\text{Yang-Zhang}} &= \sigma_{YZ} \\ &= \sqrt{\sigma_{\text{overnight volatility}}^2 + k\sigma_{\text{open to close volatility}}^2 + (1-k)\sigma_{RS}^2} \end{aligned}$$

Where:

$$k = \frac{0.34}{1.34 + \frac{N+1}{N-1}}$$

$$\sigma_{\text{overnight volatility}}^2 = \frac{1}{N-1} \sum_{i=1}^N \left[\text{Ln} \left(\frac{o_i}{c_{i-1}} \right) - \text{Ln} \left(\frac{o_i}{c_{i-1}} \right) \right]^2$$

$$\sigma_{\text{open to close volatility}}^2 = \frac{1}{N-1} \sum_{i=1}^N \left[\text{Ln} \left(\frac{c_i}{o_i} \right) - \text{Ln} \left(\frac{c_i}{o_i} \right) \right]^2$$

h_i is the high price of interval i

l_i is the low price of interval i

c_i is the close price of interval i

o_i is the open price of interval i

c_{i-1} is the close price of interval $i - 1$

4.3 Efficiency of Range-based Volatility Estimators

Shu and Zhang (2006) investigated the efficiency of the four range-based volatility estimators – the Parkinson, Garman-Klaas, Rogers-Satchell and Yang-Zhang estimators. The variance of an estimator measures the uncertainty of the estimation and the estimator with the minimum variance is determined to be the most efficient (Shu & Zhang, 2006). Using the Parkinson volatility estimator as the base case, they defined efficiency as the variance of the estimator being tested (denoted as V) relative to the variance of the Parkinson volatility estimator. A larger ratio value indicates the greater efficiency of the volatility estimator.

Equation 6

$$Eff = \frac{Var(Parkison)}{Var(V)}$$

Where:

V = variance estimator

Shu and Zhang (2006) conducted an efficiency test of the four estimators using a Monte Carlo simulation on data for the S&P 500 index. They found that using a Brownian motion path assumption with a small drift and no opening jumps, the four range estimators provided a good estimation of true variance. However, as drift increased, the Parkinson estimator and the Garman-Klaas estimator overestimated true variance. As the Rogers-Satchell and Yang-Zhang estimators are drift-independent, their efficiency was unaffected. In the case of a large opening jump, only the Yang-Zhang estimator provided a good measure of variance. The other three estimators under-estimated the variance in proportion to the size of the opening jump modelled (Shu & Zhang, 2006).

When 15-minute interval empirical data from the S&P 500 was analysed, the variances estimated with the four range-based estimators were a close proxy for the daily integrated variance using the sum of the squared returns. Shu and Zhang (2006) found, therefore, that the empirical results were supportive of the use of range-based estimators when estimating historical volatility.

4.4 Intraday Volatility Patterns

Much work on the analysis of intraday trading patterns has been conducted. It is widely accepted that there is systematic variance in trading patterns over the trading day giving rise to U-shaped, J-shaped and M-shaped patterns. These trading patterns are highly correlated with the intraday variations that take place in volatility and bid-ask spreads (Chelley-Steeley & Park, 2011).

In their work, Admati & Pfleiderer (1998), provide two basic motivations for trading, namely information and liquidity. Information traders enter or exit a trade on the basis that they have information they believe has not been incorporated into the security price. Liquidity traders, however, enter or exit positions that are unrelated to a future payoff profile but trade to achieve the necessary rebalancing required by their clients. Financial institutions tend to fall into this liquidity trader category. Liquidity traders who have some level of discretion over when they trade will choose to place orders in an environment when there is sufficient depth in the market to minimise the price impact of their trade. Admati and Pfleiderer (1998) suggest that the interaction between liquidity traders and information traders leads to pronounced patterns in markets over time. The arrival of public information and the degree of discretionary versus non-discretionary liquidity trading influences the shape of these patterns.

Foster and Viswanathan (1993) suggest that when information traders have private information, they seek to exploit that advantage during the early part of the trading day. This is before public announcements diminish that advantage (Foster & Viswanathan, 1993). Chelley-Steeley and Park (2011) refer to work conducted by French and Roll (1986) and Amihud and Mendelson (1989) to examine stock market returns following a market closure. Their findings suggest periods following a closure are 20% more volatile than during regular periods. These findings have given rise to the information accumulation hypothesis. This theory suggests information accumulates while markets are closed and that higher opening market volatility is as a result of this new information working its way into the prices (Chelley-Steeley & Park, 2011).

In an examination of the intraday pattern of information asymmetry, Tannous, Wang and Wilson (2013), found that information asymmetry is high in the morning, drops to a midday low, rises for a while in the afternoon session and then drops again thereafter (Tannous, et al., 2013).

What is clear from the available literature is the consensus that volatility is highest following a market close when the prices of securities do not incorporate accumulated information. Dependent on the interaction between various

market participants, persistent trading patterns are observed through the trading day.

Chapter 5

5 Data

5.1 MSCI Indices

MSCI Incorporated (MSCI) has been the provider of global investable market indices for over 40 years. MSCI states its objective is to construct and maintain its global equity indices in such a way that they may contribute to the international investment process by serving as (MSCI Index Research, 2014):

- Relevant and accurate benchmarks.
- The basis for asset allocation and portfolio construction across geographic markets, size-segments, style segments, and sectors.
- Effective research tools.
- The basis for investment vehicles.

5.1.1 MSCI Index Construction Methodology

There are several steps in the construction of the MSCI Global Investable Market Indices. The process begins with the definition of the investment universe and the determination and classification of the eligible securities that make up the investment universe. Mutual funds, exchange traded funds, equity derivatives, limited partnerships and most investment trusts do not qualify for inclusion in the index. MSCI undertakes a comprehensive Semi-Annual Index Review as well as a Quarterly Index Review to ensure the composition of the published indices is current, representative and investable. Each eligible security is categorised into an appropriate country group by examining the country of incorporation of the issuing company as well as the primary listing of the security. Additionally, investability requirements are considered. These include an examination of the full company market capitalisation, the free-float

adjusted market capitalisation for individual securities, annual traded value ratios (ATVR¹) and frequency of trading (FOT²). Additional investability criteria include a maximum security price of less than US\$10,000 and a minimum length of trading (3 months) except for large Initial Public Offerings (IPOs) which meet certain size criteria. (MSCI Index Research, 2014)

These steps ensure that index constituents are representative of the securities listed in a particular country group. There is therefore certainty that an MSCI index such as the MSCI Australia Index contains only securities that meet the definition of primary incorporation and listing in Australia. There is also certainty of compliance with basic liquidity requirements thus ensuring the index is investable and an investor or product provider can replicate it.

5.2 iShares MSCI Country Series

As referred to in Section 2.1, Barclays Global Investors was one of the first ETP providers to create investment products where the underlying constituents were non-domestic securities. Listed on Amex in 1996 these former BGI products that tracked the WEBS index series are now the BlackRock iShares MSCI Country Series. The series includes 57 members that have undergone additional segmentation since the initial product offering. Certain countries are now segmented by market capitalisation, for example, the iShares MSCI United Kingdom Small-Cap ETF, or by incorporating currency hedging strategies like the iShares Currency Hedged MSCI Japan ETF. For the purpose of this dissertation, the newer variants are not considered, and the examination is of the non-segmented and unhedged products. By excluding the newer variants, the ETPs under review are all based on MSCI indices that follow the construction methodology set out in Section 5.1.1. Therefore we are more able to make comparisons about the volatility profile of the ETPs with-

¹ ATVR is the average of the median daily traded value x the number of days in the month the security traded for the last 12 months annualised by multiplying by 12

² FOT is number of days a security traded versus the number of market trading days during a 3 month period

out introducing additional factors that may impact that volatility like market capitalisation or the use of derivative instruments to hedge the currency.

5.3 ETP Data

iShares MSCI Country Series ETPs data from 1 January 1998 until 11 July 2014 were obtained. The data were not uniformly available for all instruments in the sample across the period. In order to achieve a common starting point for the ETPs under review, it was decided to truncate the dataset and a date range from 1 January 2006 until 11 July 2014 is used.

For each ETP series, 15-minute interval data were obtained. As discussed in Section 4.1, the data interval selected needs to incorporate a balance between the desires for almost continuous data i.e. very high frequency and the resulting contamination by microstructure effects (Anderson, et al., 2001).

Shu and Zhang (2006) made use of 15-minute empirical data from the S&P 500 and found the variances estimated with the four range-based estimators were a close proxy for the daily integrated variance using the sum of the squared returns.

Each interval comprises of an Open, High, Low, Close and Volume metric. The Table 1 summarises the data series. Each ETP series has over 40 thousand data points for each metric. The number of observations is not completely consistent across each ETP, as there are 15-minute intervals within the trading day where a data point is missing or invalid. The generated descriptive statics provide information about the distribution of ETP prices rather than returns and so no comment can be made on the investment merits of any one ETP versus another.

Table 1: Descriptive Data for All ETPs - Jan 2006 to Jul 2014

	Open	High	Low	Close	Volume		Open	High	Low	Close	Volume
EWA: Australia						EWG: Germany					
Mean	23.39	23.42	23.35	23.39	93 834	Mean	24.75	24.78	24.72	24.75	81 869
Median	23.82	23.84	23.80	23.82	52 347	Median	23.98	24.00	23.94	23.98	32 400
Maximum	34.77	34.83	34.71	34.78	8 777 582	Maximum	36.65	36.71	36.59	36.65	12 396 873
Minimum	10.51	10.51	-	10.51	100	Minimum	12.47	12.64	12.47	12.61	100
Std. Dev.	4.03	4.03	4.04	4.03	144 718	Std. Dev.	4.98	4.98	4.99	4.98	197 737
Skewness	-0.77	-0.76	-0.77	-0.77	11	Skewness	0.27	0.28	0.27	0.27	17
Kurtosis	4.19	4.19	4.21	4.19	367	Kurtosis	2.35	2.35	2.35	2.35	585
Observations	59 021	59 021	59 021	59 021	59 021	Observations	58 948	58 948	58 948	58 948	58 948
EWC: Canada						EWH: Hong Kong					
Mean	26.78	26.81	26.75	26.78	68 974	Mean	16.91	16.93	16.88	16.91	157 215
Median	27.48	27.51	27.45	27.48	38 635	Median	16.93	16.96	16.91	16.93	84 595
Maximum	34.52	34.57	34.51	34.52	2 723 812	Maximum	24.30	24.45	24.23	24.24	33 807 988
Minimum	13.65	13.76	13.64	13.65	100	Minimum	8.38	8.54	8.36	8.37	100
Std. Dev.	3.58	3.57	3.58	3.58	102 853	Std. Dev.	2.90	2.90	2.90	2.90	294 653
Skewness	-0.94	-0.94	-0.94	-0.94	6	Skewness	-0.51	-0.50	-0.51	-0.51	37
Kurtosis	4.59	4.59	4.58	4.58	67	Kurtosis	2.93	2.93	2.94	2.93	3 504
Observations	44 994	44 994	44 994	44 994	44 994	Observations	59 322	59 322	59 322	59 322	59 322
EWD: Sweden						EWI: Italy					
Mean	27.66	27.70	27.63	27.66	8 598	Mean	19.80	19.82	19.77	19.80	23 682
Median	27.49	27.52	27.45	27.49	3 251	Median	16.96	16.99	16.93	16.96	4 750
Maximum	37.33	37.34	37.32	37.33	1 102 308	Maximum	36.53	36.55	36.40	36.40	5 679 731
Minimum	11.44	11.44	11.38	11.38	100	Minimum	9.21	9.26	9.21	9.21	100
Std. Dev.	5.34	5.34	5.34	5.34	21 533	Std. Dev.	7.82	7.82	7.81	7.82	83 485
Skewness	-0.49	-0.49	-0.49	-0.49	15	Skewness	0.80	0.80	0.80	0.80	25
Kurtosis	3.18	3.18	3.18	3.18	462	Kurtosis	2.19	2.19	2.19	2.19	1 139
Observations	42 338	42 338	42 338	42 338	42 338	Observations	52 387	52 387	52 387	52 387	52 387

	Open	High	Low	Close	Volume		Open	High	Low	Close	Volume
EWJ: Japan						EWM: Malaysia					
Mean	11.19	11.20	11.17	11.19	867 706	Mean	12.10	12.11	12.08	12.10	70 659
Median	10.70	10.71	10.69	10.70	551 345	Median	12.34	12.37	12.32	12.34	37 530
Maximum	15.54	15.55	15.53	15.55	32 187 198	Maximum	16.85	16.86	16.84	16.85	6 015 225
Minimum	6.84	6.87	6.84	6.84	100	Minimum	6.20	6.21	6.00	6.00	100
Std. Dev.	1.92	1.92	1.92	1.92	1 156 914	Std. Dev.	2.87	2.87	2.87	2.87	114 963
Skewness	0.41	0.41	0.40	0.41	6	Skewness	-0.40	-0.40	-0.40	-0.40	11
Kurtosis	1.99	1.99	2.00	1.99	88	Kurtosis	1.88	1.88	1.88	1.88	366
Observations	61 011	61 011	61 011	61 011	61 011	Observations	58 233	58 233	58 233	58 233	58 233
EWK: Belgium						EWN: Netherlands					
Mean	16.85	16.87	16.83	16.85	5 791	Mean	22.09	22.11	22.06	22.09	5 272
Median	14.58	14.59	14.57	14.58	1 400	Median	21.53	21.55	21.51	21.53	1 449
Maximum	28.57	28.64	28.57	28.63	1 303 500	Maximum	33.02	33.02	33.02	33.02	886 900
Minimum	6.61	6.66	6.27	6.61	100	Minimum	10.42	10.49	10.42	10.46	19
Std. Dev.	5.86	5.86	5.85	5.86	21 341	Std. Dev.	4.67	4.67	4.67	4.67	18 429
Skewness	0.48	0.48	0.48	0.48	20	Skewness	0.18	0.18	0.18	0.18	18
Kurtosis	1.93	1.92	1.93	1.93	728	Kurtosis	2.56	2.56	2.56	2.56	544
Observations	43 902	43 902	43 902	43 902	43 902	Observations	47 982	47 982	47 982	47 982	47 982
EWL: Switzerland						EWO: Austria					
Mean	24.54	24.56	24.51	24.54	9 004	Mean	23.79	23.82	23.76	23.79	6 654
Median	24.32	24.35	24.30	24.32	3 604	Median	20.61	20.63	20.58	20.61	1 993
Maximum	35.48	35.48	35.43	35.44	2 038 500	Maximum	41.84	48.59	41.60	41.63	1 937 100
Minimum	12.91	12.97	12.91	12.94	100	Minimum	9.32	9.49	9.32	9.43	100
Std. Dev.	4.41	4.40	4.41	4.41	27 124	Std. Dev.	8.57	8.57	8.56	8.57	23 901
Skewness	0.27	0.27	0.27	0.27	29	Skewness	0.56	0.57	0.56	0.56	26
Kurtosis	3.16	3.16	3.16	3.16	1 479	Kurtosis	1.96	1.96	1.96	1.96	1 301
Observations	55 506	55 506	55 506	55 506	55 506	Observations	49 715	49 715	49 715	49 715	49 715

	Open	High	Low	Close	Volume		Open	High	Low	Close	Volume
EWP: Spain						EWT: Taiwan					
Mean	41.50	41.55	41.44	41.50	13 368	Mean	13.21	13.22	13.19	13.21	312 770
Median	40.12	40.18	40.07	40.12	4 405	Median	13.36	13.37	13.34	13.36	191 316
Maximum	71.85	71.85	69.09	69.20	2 300 809	Maximum	18.15	18.81	18.13	18.19	12 561 777
Minimum	19.77	19.83	19.73	19.79	100	Minimum	6.42	6.50	6.42	6.45	100
Std. Dev.	10.93	10.94	10.92	10.93	34 810	Std. Dev.	2.05	2.05	2.05	2.05	392 974
Skewness	0.49	0.49	0.49	0.49	16	Skewness	-0.91	-0.90	-0.92	-0.91	5
Kurtosis	2.44	2.44	2.44	2.44	568	Kurtosis	4.52	4.51	4.53	4.52	58
Observations	55 589	55 589	55 589	55 589	55 589	Observations	59 532	59 532	59 532	59 532	59 532
EWQ: France						EWU: United Kingdom					
Mean	26.61	26.64	26.58	26.61	13 764	Mean	18.56	18.59	18.54	18.56	46 397
Median	25.81	25.83	25.79	25.81	4 100	Median	18.09	18.10	18.07	18.09	19 403
Maximum	40.09	40.74	40.04	40.09	2 660 700	Maximum	27.35	27.50	27.29	27.38	8 636 987
Minimum	14.39	14.44	14.39	14.44	100	Minimum	8.90	9.00	8.88	8.97	100
Std. Dev.	5.81	5.81	5.81	5.81	48 357	Std. Dev.	3.65	3.65	3.65	3.65	130 974
Skewness	0.52	0.52	0.52	0.52	18	Skewness	0.05	0.06	0.04	0.05	21
Kurtosis	2.44	2.44	2.44	2.44	538	Kurtosis	2.67	2.66	2.67	2.67	814
Observations	54 408	54 408	54 408	54 408	54 408	Observations	57 797	57 797	57 797	57 797	57 797
EWS: Singapore						EWW: Mexico					
Mean	11.85	11.87	11.83	11.85	91 883	Mean	54.05	54.14	53.97	54.06	104 301
Median	12.51	12.53	12.49	12.51	52 874	Median	56.08	56.18	55.97	56.08	74 126
Maximum	15.99	15.99	15.93	15.96	6 822 000	Maximum	76.74	76.80	76.67	76.74	2 092 172
Minimum	5.20	5.22	5.18	5.21	100	Minimum	21.57	21.64	21.52	21.58	100
Std. Dev.	2.14	2.14	2.14	2.14	133 533	Std. Dev.	11.40	11.40	11.41	11.40	104 051
Skewness	-1.04	-1.04	-1.04	-1.04	9	Skewness	-0.63	-0.63	-0.63	-0.63	3.43
Kurtosis	3.33	3.33	3.34	3.33	222	Kurtosis	2.73	2.73	2.73	2.73	25.14
Observations	58 710	58 710	58 710	58 710	58 710	Observations	55 552	55 552	55 552	55 552	55 552

	Open	High	Low	Close	Volume
EWY: South Korea					
Mean	52.65	52.72	52.57	52.65	93 383
Median	54.54	54.62	54.46	54.55	59 552
Maximum	74.82	75.05	74.73	74.84	6 247 681
Minimum	19.00	19.00	19.00	19.00	100
Std. Dev.	10.22	10.21	10.23	10.22	113 418
Skewness	-0.89	-0.89	-0.90	-0.89	7
Kurtosis	3.69	3.69	3.70	3.70	197
Observations	59 096	59 096	59 096	59 096	59 096
EWZ: Brazil					
Mean	60.97	61.11	60.83	60.97	523 193
Median	59.91	60.07	59.75	59.90	407 374
Maximum	101.24	102.21	100.98	101.24	8 719 762
Minimum	26.89	27.20	26.64	26.90	100
Std. Dev.	14.26	14.28	14.24	14.26	453 318
Skewness	0.09	0.10	0.09	0.09	3
Kurtosis	2.36	2.35	2.36	2.36	17
Observations	53 114	53 114	53 114	53 114	53 114
IVV: United States					
Mean	134.01	134.15	133.87	134.01	116 439
Median	133.07	133.20	132.91	133.06	77 722
Maximum	199.55	199.57	199.49	199.54	6 268 158
Minimum	67.33	67.52	67.22	67.33	100
Std. Dev.	25.72	25.69	25.75	25.72	149 539
Skewness	0.19	0.19	0.19	0.19	8
Kurtosis	3.07	3.07	3.07	3.07	156
Observations	60 606	60 606	60 606	60 606	60 606

5.4 Foreign Exchange Data

As all the ETPs under review are listed and trade on the New York Stock Exchange (NYSE), the data metrics are all denominated in United States Dollars (USD). As these ETP instruments represent an underlying basket of foreign-listed (i.e. non-US) equity securities, a foreign exchange effect is implicit in the USD price. To provide for the examination of this effect on the results, the foreign exchange currency rates for the USD and the currency appropriate to the underlying instrument basket were sourced. Unfortunately, intraday foreign exchange data for the full date range was unavailable, and the foreign exchange data runs from 28 September 2009 to 11 July 2014 in 15-minute time intervals during the NYSE trading day. The analysis of the impact of currency on the results of the volatility tests will therefore be restricted to this period.

The descriptive foreign exchange data are found in Table 2. Several currencies display an almost parity relationship with the USD over the time frame consider. The Australian Dollar, Canadian Dollar and Swiss Franc have mean values of 1.041, 1.040 and 0.946 respectively. The characteristics of the various currency pairs are examined further in Chapter 8.

Table 2: Descriptive Data for Foreign Exchange Pairs versus United State Dollar - Sep 2009 to Jul 2014

	Open	High	Low	Close		Open	High	Low	Close
AUD: Australian Dollar					EUR: Euro				
Mean	1.041	1.042	1.040	1.041	Mean	0.754	0.754	0.753	0.754
Median	1.020	1.021	1.019	1.020	Median	0.750	0.750	0.750	0.750
Maximum	1.321	1.323	1.320	1.321	Maximum	0.956	0.956	0.955	0.955
Minimum	0.904	0.905	0.903	0.904	Minimum	0.660	0.660	0.660	0.660
Std. Dev.	0.088	0.088	0.088	0.088	Std. Dev.	0.044	0.044	0.044	0.044
Skewness	0.860	0.860	0.858	0.860	Skewness	0.966	0.970	0.960	0.966
Kurtosis	3.243	3.242	3.236	3.242	Kurtosis	5.394	5.406	5.375	5.395
Observations	33 748	33 748	33 748	33 748	Observations	37 164	37 164	37 164	37 164
BRL: Brazilian Real					GBP: Great British Pound				
Mean	2.006	2.007	2.005	2.006	Mean	0.630	0.630	0.630	0.630
Median	1.988	1.989	1.987	1.988	Median	0.629	0.629	0.629	0.629
Maximum	3.302	3.302	3.296	3.302	Maximum	0.701	0.702	0.701	0.701
Minimum	1.531	1.531	1.531	1.531	Minimum	0.582	0.582	0.582	0.582
Std. Dev.	0.320	0.321	0.320	0.320	Std. Dev.	0.021	0.021	0.021	0.021
Skewness	0.877	0.878	0.876	0.877	Skewness	0.247	0.249	0.246	0.247
Kurtosis	3.670	3.675	3.666	3.671	Kurtosis	2.926	2.934	2.916	2.926
Observations	36 091	36 091	36 091	36 091	Observations	37 135	37 135	37 135	37 135
CAD: Canadian Dollar					HKD: Hong Kong Dollar				
Mean	1.040	1.041	1.040	1.040	Mean	7.763	7.763	7.763	7.763
Median	1.027	1.028	1.027	1.027	Median	7.758	7.758	7.757	7.758
Maximum	1.282	1.282	1.280	1.282	Maximum	7.810	7.811	7.809	7.810
Minimum	0.942	0.943	0.941	0.942	Minimum	7.749	7.749	7.749	7.749
Std. Dev.	0.060	0.060	0.060	0.060	Std. Dev.	0.013	0.013	0.013	0.013
Skewness	1.579	1.580	1.577	1.580	Skewness	1.257	1.252	1.259	1.254
Kurtosis	6.207	6.216	6.193	6.207	Kurtosis	3.624	3.613	3.623	3.616
Observations	37 165	37 165	37 165	37 165	Observations	37 123	37 123	37 123	37 123
CHF: Swiss Franc					KWR: South Korean Won				
Mean	0.946	0.947	0.945	0.946	Mean	1108.57	1108.93	1108.21	1108.57
Median	0.934	0.935	0.934	0.934	Median	1112.10	1112.40	1111.80	1112.10
Maximum	1.167	1.168	1.164	1.167	Maximum	1255.80	1256.30	1255.80	1255.80
Minimum	0.710	0.716	0.707	0.710	Minimum	1007.43	1008.00	1006.95	1007.55
Std. Dev.	0.066	0.066	0.066	0.066	Std. Dev.	45.24	45.19	45.30	45.24
Skewness	0.602	0.608	0.598	0.603	Skewness	0.09	0.09	0.09	0.09
Kurtosis	4.059	4.056	4.062	4.060	Kurtosis	2.82	2.82	2.82	2.82
Observations	37 150	37 150	37 150	37 150	Observations	38 430	38 430	38 430	38 430

	Open	High	Low	Close		Open	High	Low	Close
JPY: Japanese Yen					SEK: Swedish Krona				
Mean	88.19	88.24	88.14	88.19	Mean	6.842	6.848	6.835	6.842
Median	85.91	85.95	85.85	85.91	Median	6.703	6.708	6.696	6.702
Maximum	105.39	105.42	105.33	105.38	Maximum	8.822	8.827	8.799	8.825
Minimum	75.67	75.70	75.66	75.68	Minimum	5.980	5.984	5.971	5.977
Std. Dev.	8.93	8.94	8.92	8.93	Std. Dev.	0.476	0.477	0.475	0.476
Skewness	0.37	0.37	0.37	0.37	Skewness	1.445	1.446	1.443	1.446
Kurtosis	1.71	1.71	1.71	1.71	Kurtosis	5.241	5.237	5.243	5.244
Observations	32 474	32 474	32 474	32 474	Observations	37 191	37 191	37 191	37 191
MYR: Malaysian Ringgit					SGD: Singapore Dollar				
Mean	3.183	3.185	3.182	3.183	Mean	1.286	1.286	1.285	1.286
Median	3.160	3.161	3.159	3.160	Median	1.267	1.268	1.267	1.267
Maximum	3.721	3.721	3.720	3.721	Maximum	1.423	1.424	1.423	1.423
Minimum	2.922	2.923	2.897	2.897	Minimum	1.200	1.200	1.200	1.200
Std. Dev.	0.149	0.150	0.149	0.149	Std. Dev.	0.057	0.057	0.057	0.057
Skewness	1.055	1.049	1.058	1.055	Skewness	0.937	0.935	0.938	0.937
Kurtosis	4.022	4.008	4.029	4.022	Kurtosis	2.681	2.679	2.681	2.681
Observations	36 922	36 923	36 922	36 923	Observations	37 106	37 106	37 106	37 106
MXN: Mexican Peso					TWD: New Taiwan Dollar				
Mean	12.805	12.815	12.794	12.805	Mean	30.180	30.184	30.177	30.181
Median	12.868	12.878	12.858	12.868	Median	29.950	29.954	29.950	29.950
Maximum	14.446	14.462	14.427	14.444	Maximum	32.570	32.600	32.570	32.600
Minimum	11.489	11.498	11.481	11.483	Minimum	28.530	28.530	15.015	28.520
Std. Dev.	0.532	0.534	0.531	0.532	Std. Dev.	1.028	1.027	1.031	1.028
Skewness	-0.177	-0.173	-0.186	-0.178	Skewness	0.709	0.706	0.615	0.708
Kurtosis	3.075	3.076	3.076	3.076	Kurtosis	2.401	2.399	3.697	2.402
Observations	32 786	32 786	32 786	32 786	Observations	35 386	35 386	35 386	35 386

5.5 Global Exchange Hours

Due to varying time zones across global stock exchanges, it was important to gather the opening and closing times of the exchanges on which the underlying components of the ETPs under review trade. As the ETP instruments are listed on the NYSE, all global opening and closing times were converted to the time zone application to the NYSE, namely Eastern Standard Time (EST). For the sake of clarity, all trading times mentioned in the analysis are quoted in EST. Figure 2 below provides a visual representation of the non-overlapping, partially over-lapping and completely overlapping global exchange trading hours in EST.

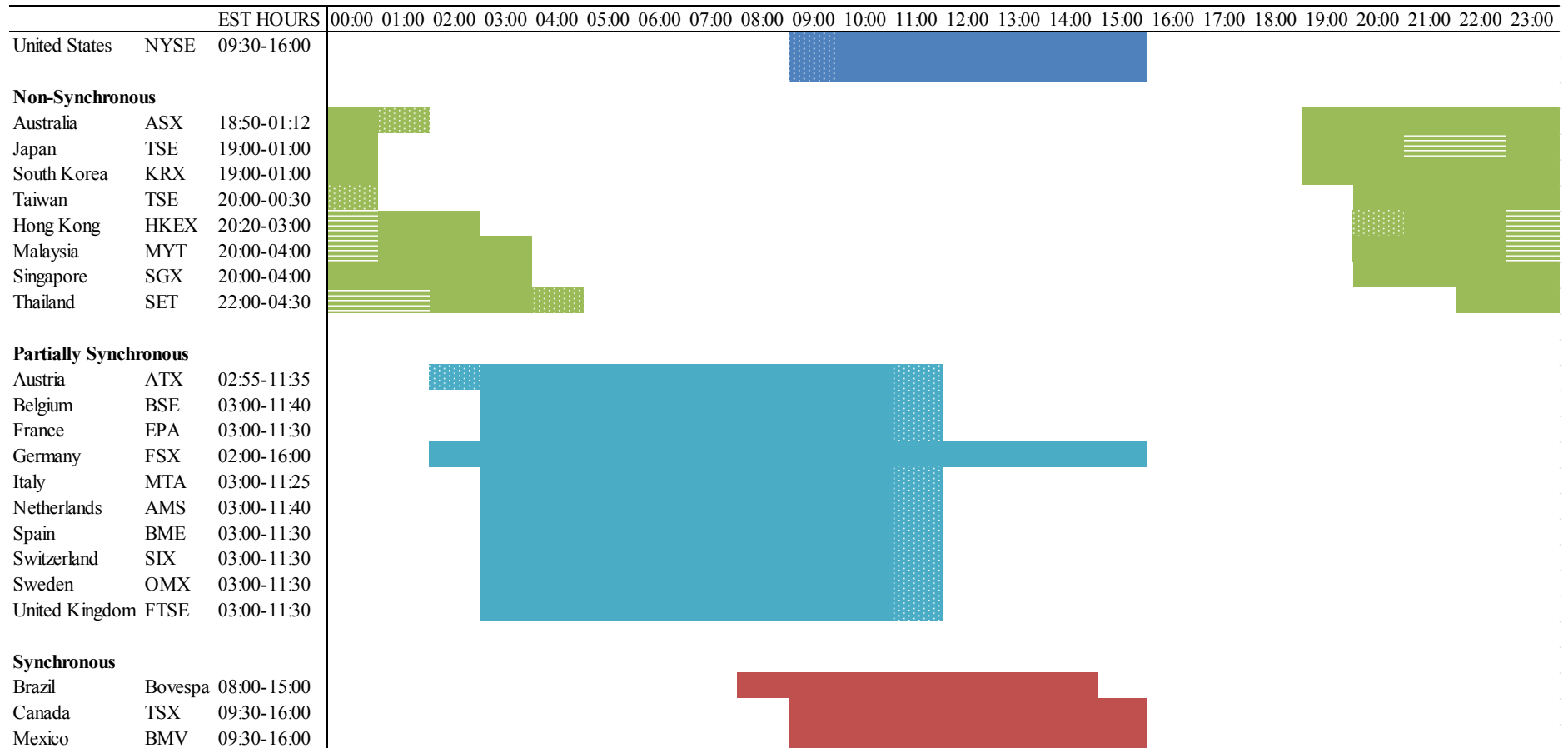
The ETPs under review are categorised into three groups based on the exchange hours of the underlying securities in their respective baskets. These groups are non-synchronous, partially synchronous and synchronous. The characteristics of the members of these three groups are closely examined.

Hours that display a striped pattern in Figure 2 rather than a solid fill denote closed periods during the trading day. Asian stock exchanges typically close over the lunch period, for example, reviewing the hours of 21:00 to 22:00 EST for the Japanese Tokyo Stock Exchange reflects the closure for lunch.

Hours that display a dotted pattern in Figure 2 rather than a solid fill denote an opening or closing of that exchange part-way through the hour. For example, examining the hour of 11:00 to 12:00 EST reflects the closing of the European markets part-way through that hour.

As identified in Figure 2, the Australasian markets exhibit no overlapping trading hours with the New York market – they are non-synchronous. The European markets, however, are still open during the first part of the New York trading day and close predominantly at 11:30 EST. The material exception in this partially synchronous group is the German market. The Frankfurt Stock Exchange maintains a specialist trading service until 20:00 Central European Time (CET) or 16:00 EST. The exchanges in North and South America have almost totally over-lapping or synchronous trading hours with the NYSE.

Figure 2: Global Exchange Hours in Eastern Standard Time



Chapter 6

6 Empirical Analysis

6.1 Methodology

The empirical work commences with a computation and analysis of the intraday 15-minute interval, range-based volatility for each ETP in the universe under review. Having computed the volatility data, an initial, high-level analysis to understand the key features of the dataset is undertaken. Armed with an initial understanding, the characteristics of the data distribution can be determined through testing for normality and stationarity. The results of this testing are then incorporated in the next steps in the research methodology.

As the ultimate research objective is to determine whether a difference exists in the volatility profile between the ETP groups as categorised in Section 5.5, we need to work towards an appropriate test that meets the research objective. The methodology applied in meeting this objective, is a function of the early findings and hence needs to incorporate a “decision-tree” element, where the prior path and findings dictate the next methodological choices.

As such, the research methodology cannot be mapped out in advance, but is embedded within the research process and is ultimately contingent upon various outcomes at each stage in the process.

6.2 Range-based Volatility Computations

For each ETP following the iShares MSCI Country Index Series in the dataset under review, the following values were obtained for each 15-minute interval of the NYSE trading day, generating 26 intervals per day:

- Open price

- Close price
- High price
- Low price
- Volume of shares traded

In the examination of range-based volatility measures outlined in Section 4.2, the inputs to the range-based volatility measures can be seen to be the open, close, prior close, high and low prices. Typically, the inputs into the determination of range-based volatility are the open, close, high and low prices generated over the course of the trading day rather than for an intraday interval within the trading day. However, in this study, the inputs used are the open, close, high, low and prior period close values for each 15-minute time interval. Using these intraday data-points allows for an estimation of range-based volatility for each of the 26, 15-minute intervals, during the New York Stock Exchange trading day. Using high-frequency 15-minute intraday data allows for a robust estimation of the underlying volatility effects that may be lost if daily data was selected, but is not so high-frequency as to become distorted by market microstructure noise.

The range based methodologies presented in Section 4.2 are all typically applied to daily data. While the Yang-Zhang extension presented in Equation 5 is robust against overnight jumps and drift, it is best-suited for daily data as it incorporates the sum of the estimated overnight variance, the estimated opening market variance and the Rogers-Satchell drift independent estimator. This thesis instead uses intraday data in order to compute a range-based volatility measure for each 15-minute interval within the trading day. The range-based methodology adopted is the Yang-Zhang-Garman-Klaas extension that includes an ability to incorporate overnight jumps, but assumes zero drift and is set out in Equation 4 (Bennett & Gil, 2012).

Using a programmatic routine in EViews statistical software, the range-based volatility for each 15-minute interval of each trading day for every ETP instrument under review was computed. A range-based volatility measure for each 15-minute interval is found by aggregating the range-based metric across each 15-minute interval over the entire date range. By way of example, all of

the range-based metrics from the 9:30am to 9:45am time interval for each trading day were aggregated. This aggregated data were used to determine a range-based volatility measure for that 15-minute intraday time interval over the entire date range. This procedure was repeated for each 15-minute time interval and each ETP under review.

6.3 Initial Data Analysis

Before undertaking any meaningful statistical analysis, the inherent characteristics of the dataset must be understood. As such, we first conduct some preliminary visual analysis before undertaking more traditional statistical testing methods.

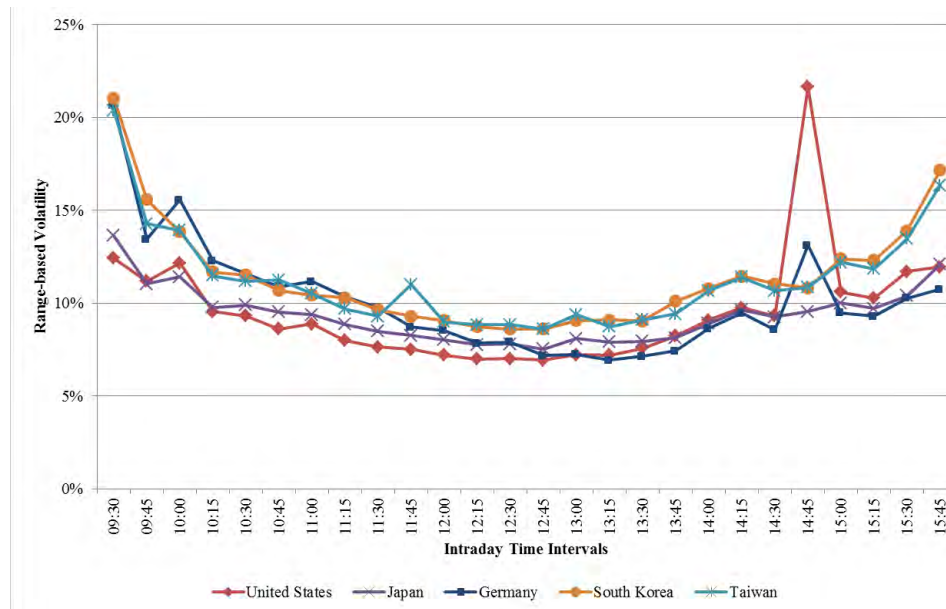
In the initial visual analysis presented Section 6.3.1, the 15-minute intraday range-based volatility data were aggregated and summarised. This aggregation was conducted for each time interval across the entire data sample date range to present the intraday pattern of volatility which persists for the ETP instruments. However, by using the raw intraday data which is non-aggregated and non-summarised, we generate a sample of intraday range-based volatility for each ETP instrument. These data consist of a numerical range-based volatility measure for each of the 26, 15-minute time intervals on each trading day.

6.3.1 Visual Analysis - Intraday Pattern

Visually in Figure 3, we see evidence of a U-shaped intraday volatility pattern in the ETPs selected for initial review. These ETPs are selected on the basis of their NAV on 30 March 2015 and constitute the five largest ETPs within the ETP universe specified in Section 5.2. Volatility, as measured by the range-based Yang-Zhang-Garman-Klaas extension over the period January 2006 to July 2014 appears to be elevated in the 30-45 minutes after NYSE opening. It drops off over the mid-day period and then rises to the afternoon close. As ETPs trade on the exchange in the same manner as equity securities, we would expect them to exhibit a similar systematic variance to that of

securities. This characteristic also gives rise to identifiable volatility patterns through the trading day.

Figure 3: Range-based Volatility Measure of Select ETPs - Jan 2006 to Jul 2014



6.3.2 Apparent Anomaly at 2:45pm to 3:00pm

Again, on visual review of Figure 3, we note what appears to be a data anomaly during the 2:45pm to 3:00pm time interval. For the ETP representing the basket of US stocks and less so for the ETP representing the basket of German stocks, the anomaly is particularly pronounced. The other ETPs assessed in this initial review do not show visual evidence of the anomaly. Upon investigation, it was determined that the unanticipated rise in volatility was as a consequence of one outlying data point generated on 6 May 2010. This rise was observed most markedly in ETPs tracking a US domestic basket, during the 2:45pm to 3:00pm time interval. On that day, during the afternoon trading session, US equity markets underwent the “Flash Crash”.

6.3.2.1 Flash Crash

The “Flash Crash” event was the largest one-day point decline ever experienced in the history of the Dow Jones Industrial Average, which is arguably the bellwether index for US stocks. Of the 8 000 individual equity and

ETP instruments traded that day, many experienced rapid declines of up to 15 percent only to recover most of their losses within the day. Over 20 000 trades across more than 300 securities were executed at prices more than 60 percent away from their values (Staffs of the CFTC and SEC, 2010). In the aftermath of the Flash Crash, several immediate explanations were provided, but the consensus was that the Flash Crash was largely a liquidity crisis (Easley, et al., 2011). The market backdrop of the day was one of bearish sentiment. There were concerns in the US market about the severity of the European debt crisis and the increased probability of a Greek default on sovereign debt. The Euro declined sharply against other currency majors, notably, the US Dollar and Japanese Yen.

The two most active instruments traded electronically on the NYSE are the E-mini S&P 500 futures contracts and SPDR, the Exchange Traded Fund representing the S&P 500 basket, under the ticker SPY. Both instruments were suffering from low liquidity and high volatility during the morning trading session. Just after 2:30pm, an institutional trader initiated an automated execution trading algorithm to sell over US\$4 billion of E-mini contracts. The execution rate was set as a function of market volume in the prior minute. High-Frequency Traders (HFT) were the initial purchasers of the sell order, but minutes later became sellers themselves to reduce their long positions. This participation by the HFTs increased trading and generated higher volume minute-by-minute. The increased volume became a positive feedback loop for the institutional automated trade forcing the sale of E-mini contracts at an accelerating rate into the market. The automated E-mini trade took just 20 minutes to execute whereas a similar E-mini trade placed the year before had taken 5 hours to execute. The combined selling pressure from the institutional trader and the HFTs forced the E-mini prices downwards incredibly rapidly.

In response to the withdrawal of liquidity in the E-minis and the rapidly falling prices, automated trading systems used by market participants temporarily “paused”. This pause caused a lack of liquidity in equity and ETP instruments and a widening of spreads. The widespread distortion in equity prices that make up the ETP underlying baskets meant the natural arbitrage

mechanisms that work to maintain ETP prices close to NAV were interrupted. This interruption pushed ETP prices far from NAV (Madhavan, 2012).

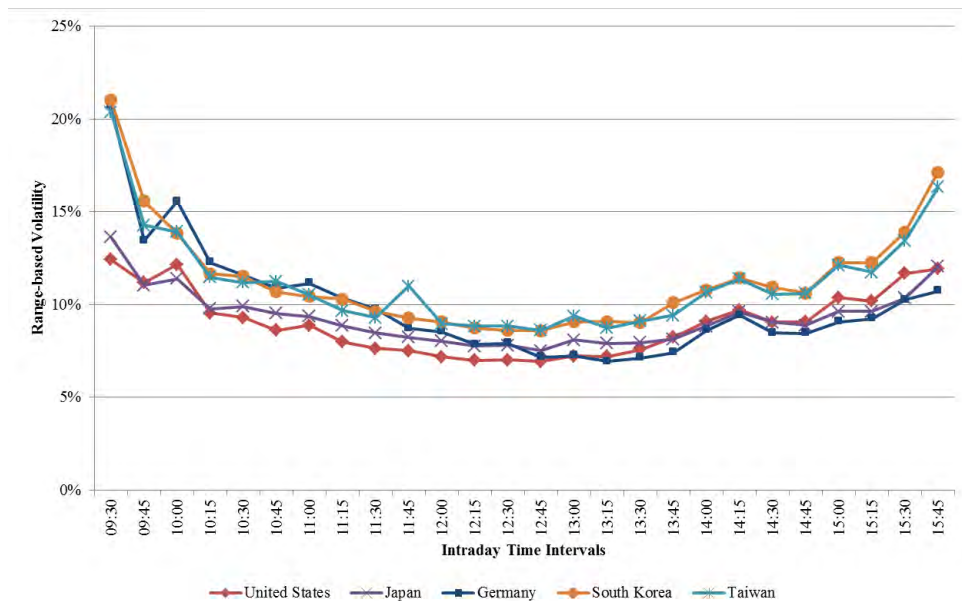
The uncertainty in establishing a fair value price for many equities and ETPs interrupted automated trading. The low liquidity and resulting high volatility profoundly affected the smooth functioning of the US equity market for a brief period. Subsequent to the Flash Crash event, policy makers have rushed to impose new trading rules and “circuit breakers” to prevent a similar future occurrence.

6.3.3 Data Adjustment

In response to the Flash Crash event which has such an obvious distortive effect on the dataset, a decision was made to exclude the 6 May 2010 trading day from the dataset for all ETPs. This exclusion is made irrespective of the listing geography of their underlying basket. After filtering out that data point, the programmatic routine to calculate the range-based volatility for each 15-minute interval on each trading day for each ETP instrument was rerun. Figure 4 below shows the constituents of the same initial review basket, selected on the basis of their NAV on 30 March 2015.

The removal of the Flash Crash data has resulted in the elimination of the observable spike in volatility during the 2:45pm to 3:00pm intraday interval. For all further empirical work, the Flash Crash data are excluded.

Figure 4: Range-based Volatility Measure of Select ETPs - Jan 2006 to Jul 2014 Excluding Flash Crash



6.4 Data Profile and Testing

6.4.1 Descriptive Statistics

The dataset comprises of the computed range-based volatility metrics for each 15-minute time interval for each ETP over the historical sample range. The sample range is 1 January 2006 to 11 July 2014. As presented above, we can aggregate these data into one set for each instrument comprising of intraday data, or look at each 15-minute time interval for each ETP as 26 sets of data per ETP per day. In certain instances, it is appropriate to make use of the aggregated dataset and in others it is more appropriate to use the individual time slices as distinct datasets. The descriptive statistics presented below make use of the aggregated data to provide some scale and context for the numerical results and analysis to follow.

**Table 3: Descriptive Statistics of Range-Based Volatility for all ETPs - Jan 2006 to Jul 2014
- Aggregated Data**

Ticker	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
EWA	6.10E-06	1.82E-06	0.003	0	2.93E-05	52.287	4596.181	54 428
EWC	3.60E-06	1.39E-06	0.001	0	9.71E-06	30.487	2313.777	41 604
EWD	3.98E-06	1.30E-06	0.007	0	3.53E-05	172.993	32477.220	38 576
EWG	5.15E-06	1.40E-06	0.007	0	5.57E-05	101.048	11754.530	54 421
EWH	5.39E-06	1.59E-06	0.003	0	2.68E-05	55.226	4874.495	54 615
EWI	4.34E-06	1.36E-06	0.002	0	1.51E-05	43.701	3747.001	45 681
EWK	5.45E-06	9.21E-07	0.012	0	8.27E-05	110.752	14834.280	34 437
EWL	3.41E-06	8.94E-07	0.001	0	1.27E-05	33.094	2168.839	50 744
EWM	5.68E-06	1.45E-06	0.013	0	6.83E-05	138.373	23835.530	54 002
EWN	3.35E-06	6.94E-07	0.008	0	4.76E-05	148.238	25576.000	39 447
EWO	6.09E-06	1.10E-06	0.013	0	0.000101	99.037	11010.930	42 428
EWP	4.59E-06	1.43E-06	0.004	0	3.92E-05	89.230	9163.500	50 474
EWQ	3.70E-06	1.02E-06	0.006	0	3.24E-05	161.422	31189.970	48 876
EWS	5.88E-06	1.74E-06	0.012	0	6.52E-05	147.714	25774.940	54 306
EWT	6.31E-06	1.97E-06	0.003	0	3.04E-05	49.058	3971.330	54 709
EWU	4.90E-06	1.45E-06	0.007	0	4.97E-05	108.782	14196.340	53 660
EWV	7.03E-06	2.29E-06	0.006	0	4.12E-05	71.643	7873.601	54 114
EWY	6.56E-06	1.67E-06	0.004	0	3.53E-05	55.336	5345.410	54 500
EWZ	1.59E-05	4.55E-06	0.015	0	0.000111	78.647	9024.781	47 763
IVV	3.99E-06	1.10E-06	0.002	0	1.73E-05	44.581	3819.673	55 043

As is evident from Table 3, the lower bound, or minimum value is zero as volatility takes positive values only. This zero minimum introduces a positive skewness to the data that statistical testing must accommodate. Statistical tests make assumptions about the distribution of the data under review and the most typical assumption is one of normality. A violation of the normality assumption adds additional complexity to the testing process, a violation commonly present in financial data.

While the mean and median values presented in Table 1 are small, it must be remembered these reflect the mean and median of a range-based volatility measure over just 15-minutes of trading. Typically, financial instrument volatility is presented as a daily or annualised number.

6.4.2 Characteristics of the Data Distribution

Understanding the characteristics of an empirical data distribution is highly important prior to conducting any statistical testing. The validity of sta-

tistical tests is reliant on the data conforming to various distribution assumptions.

The determination of normality is typically one of the first steps performed when analysing empirical data. When conducting parametric statistical analysis, there is an assumption that the data are normally distributed. If this assumption is violated, then the interpretation of the statistical results may not be valid.

Testing for stationarity is another initial step typically undertaken ahead of performing empirical data analysis. For data to be considered stationary, the mean, variance and covariance of the data must not vary as a function of time. Financial time series data often exhibit trending behaviour or a non-stationary mean.

The following Sections, 6.4.3 and 6.4.4 cover these two preliminary areas of statistical testing and allow for appropriate choices to be made in selecting further statistical test procedures.

6.4.3 Testing for Normality

Typically normality tests are undertaken in three ways; visual observation of graphical output, numerical methods and formal normality tests.

The four most commonly used tests for normality are the Shapiro-Wilk test, the Kolmogorov-Smirnov test, the Lilliefors test and the Anderson-Darling test. Razali and Wah undertook a 2011 study to determine the power of these four formal tests of normality. They found the Shapiro-Wilk test outperformed the other normality tests across a range of simulated distributions including symmetric, non-normal and asymmetric simulated distributions (Razali & Wah, 2011).

Additionally to the four commonly used normality tests mentioned above, there are also normality tests that focus on the moments of the distribution. While the mean and the standard deviation of a distribution provide information about the distribution characteristics, the skewness and kurtosis are additional important measures. Only testing for the skewness or kurtosis individually does not necessarily provide robust information on the shape of the

distribution. A test which combines both the skewness and kurtosis metrics into a so called “omnibus” test provides can provide useful insight into the distribution shape. The two most often used moment tests are the D’Agostino-Pearson test and the Jarque-Bera test.

The Jarque-Bera test is widely used, particularly in assessing the distributions of economic data. The prevalence of the Jarque-Bera test is due mostly to its ease of computation. Thadewald and Büning (2004) showed that the Jarque-Bera test performed well when the distribution under review was symmetric with medium to long tails and for slightly skewed distributions with long tails. The Jarque-Bera test displayed poor power in instances where the distribution had short tails, particularly if the distribution shape was bimodal. (Thadewald & Büning, 2004)

Due to the different normality testing approaches of the Shapiro-Wilk and Jarque-Bera tests their respective results are complimentary. Both tests will be applied to the dataset under review in this study to determine whether the data are normally distributed. The Jarque-Bera test is selected despite its potential shortcomings in certain circumstances due to its widespread use and therefore interpretative ease.

6.4.3.1 Shapiro-Wilk Test

Shapiro and Wilk proposed the test in 1965 and it was the first test of its type to detect departures from normality due to either skewness or kurtosis or both. A visual version of a Shapiro-Wilk test would be to examine the linearity of the empirical data sample using a Q-Q plot and to compute the correlation coefficient. The Shapiro-Wilk test is essentially a formal version of this analysis based on the correlation between the data under review and the corresponding normal scores. The null hypothesis of the Shapiro-Wilk test is that the population data are normally distributed. The test statistic is given as:

Equation 7

$$W = \frac{(\sum_{i=1}^N a_i y_i)^2}{\sum_{i=1}^N (y_i - y^*)^2}$$

Where:

y_i is the i^{th} order statistic

y^* is the sample mean

$$a_i = (a_1, \dots, a_N) = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{1/2}}$$

$m = (m_1, \dots, m_N)^T$ are the expected values of the order statistics of iid random variables sampled from the standard normal distribution

V is the covariance matrix of those order statistics

6.4.3.2 Jarque-Bera Test

The Jarque-Bera test is essentially a goodness-of-fit test that determines whether the sample data have a skewness and kurtosis matching that of a normal distribution. The null hypothesis is that the population data are normally distributed meaning the skewness and excess kurtosis are zero. The Jarque-Bera test statistic is given as:

Equation 8

$$JB = \frac{n}{6} \left(S^2 + \frac{1}{4} (K - 3)^2 \right)$$

Where:

S = skewness

K = kurtosis

6.4.3.3 Results of Testing for Normality

The selected normality tests, namely the Shapiro-Wilk test and the Jarque-Bera test were conducted on the non-aggregated range-based volatility results for each 15-minute time interval for each ETP instrument. The full tabular results are presented in Appendix A.1 and A.2. For each 15-minute time interval for each ETP, the results generated by both the Shapiro-Wilk test and the Jarque-Bera test, show the data to be distinctly non-normal in distribution.

All of the *p-values* associated with the test statistics are zero. This can be interpreted as a rejection of the null hypothesis that the data are normally distributed at all confidence levels. This finding means that any additional statistical testing or interpretation has to account for this non-normality.

6.4.4 Testing for Stationarity

For data to be considered stationary, the mean, variance and covariance of the data must not vary as a function of time. Financial time series data often exhibit trending behaviour or a non-stationary mean. If the data are trending, then a form of trend removal is required prior to analysis work being conducted and this trend removal takes the form of first-differencing or time-trend regression. Unit root tests can be conducted to determine if the trend is stochastic, through the presence of a unit root, or deterministic through the presence of a polynomial time trend (Phillips & Perron, 1988). Financial time series data often have a complicated structure and as such, the Augmented Dickey-Fuller or the Phillips-Perron Unit Root tests are recommended in such cases (Zivot, 2006).

6.4.4.1 Dickey-Fuller Test Background

Commonly used in econometric and financial data empirical analysis is the Augmented Dickey-Fuller (ADF) test. The precursor to the ADF test is the Dickey-Fuller test proposed by Dickey and Fuller in 1979.

Considering an autoregressive, AR(1), pure random walk model with the following form:

Equation 9

$$Y_t = \rho Y_{t-1} + \varepsilon_t \text{ where } t = 1, 2, \dots, n$$

Where:

$$Y_0 = 0 \text{ and } \varepsilon_t = iid[0, \sigma^2]$$

The time series Y_t converges (as $t \rightarrow \infty$) to a stationary time series if $|\rho| < 1$. If $|\rho| = 1$, the time series is not stationary and the variance of the time series grows exponentially as t increases (Fuller & Dickey, 1979).

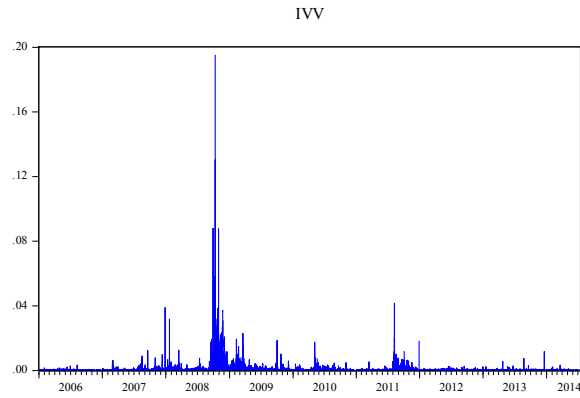
Intuitively, if a time series is stationary, there is a tendency to return to a constant mean such that a positive value in the series is followed by a negative value and vice versa. The current level of the series is a good predictor of the next period's change.

The Augmented Dickey-Fuller test is an extension of the Dickey-Fuller test, which allows for the removal of any autocorrelation in the time series prior to testing. In both tests, the test statistic is compared with a Dickey-Fuller critical value. If the test statistic is more negative (i.e. a lower value) than the Dickey-Fuller critical value, then the null hypothesis is rejected. No unit root is present and the time series is stationary.

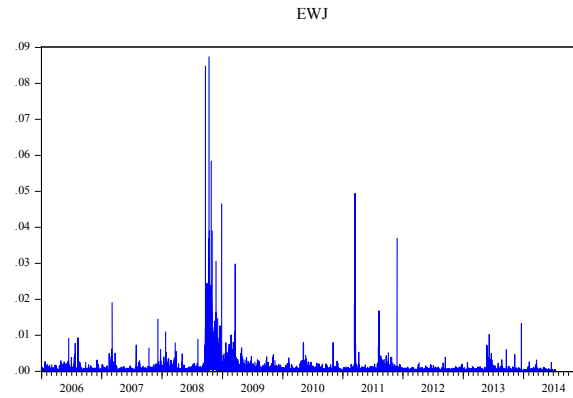
The Dickey-Fuller test and the ADF test apply to random walk models that include drift and also a deterministic or time-dependent linear trend. Baltagi (2011) quotes Maddala (1992) in advising the use of visual inspection of the data as well as conducting more formal testing (Baltagi, 2011). The visual assessment of the data under review suggests that neither drift nor a time trend is present, and these additional terms are excluded in the testing process. The charts below reflect the range-based volatility for the select group of ETPs as identified in Section 6.3.1.

Figure 5: Range-based Volatility for Select ETPs - Jan 2006 to July 2014 - Aggregated Data

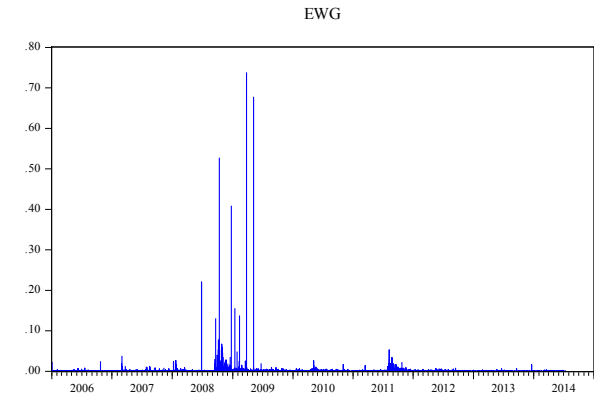
United States: IVV



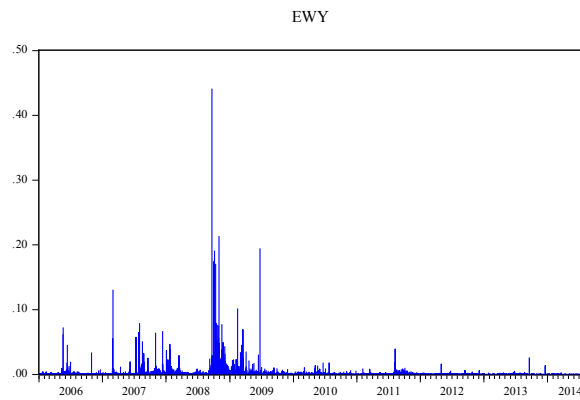
Japan: EWJ



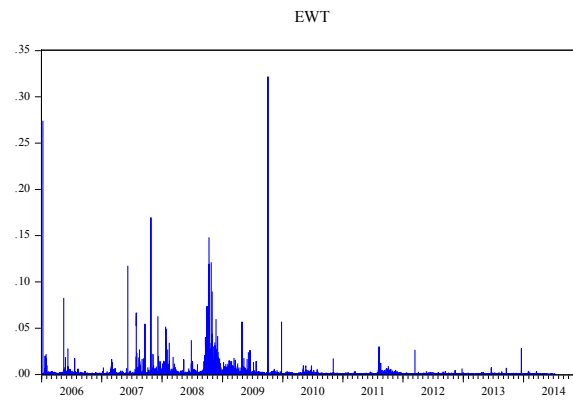
Germany: EWG



South Korea: EWY



Taiwan: EWT



6.4.4.1.1 Dickey-Fuller Test

If we have an AR(1) model as below:

Equation 10

$$\Delta y_t = \delta y_{t-1} + \varepsilon_t$$

Where:

$$Y_0 = 0 \text{ and } \varepsilon_t = iid[0, \sigma^2]$$

We are unable to make use of the Central Limit Theorem³ and conventional t-test statistics in testing for values of δ in the event that y_t and y_{t-1} are non-stationary. Instead, we make use of the Dickey-Fuller asymptotic distribution to compare the t-statistic with a Dickey-Fuller critical value. The testing hypothesis is given as:

$$H_0: \delta = 1 \text{ (unit root, non-stationary)}$$

$$H_1: \delta < 1 \text{ (stationary)}$$

If we accept the null hypothesis with $\delta = 1$, this results in an AR(1) process with a unit root and one which is non-stationary. We would visually observe trends in the data over time.

6.4.4.1.2 Augmented Dickey-Fuller Test

For a process that is more complex than an AR(1) model, an AR(n) process can be given with the form:

Equation 11

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^h \beta_i \Delta y_{t-i} + \varepsilon_t$$

Where:

$$Y_0 = 0 \text{ and } \varepsilon_t = iid[0, \sigma^2]$$

Again, the testing hypothesis is given as:

$$H_0: \delta = 1 \text{ (unit root, non-stationary)}$$

³ The sampling distribution of a statistic will follow a normal distribution, as long as the sample size is sufficiently large

$H_1: \delta < 1$ (stationary)

If we accept the null hypothesis with $\delta = 1$ results in an AR(n) process with a unit root and one which is non-stationary. If we reject the null hypothesis, we find $\delta < 1$ and can conclude our time series is stationary.

6.4.4.1.2.1 Determination of Lags

In dealing with a more complex AR(n) process, we need to determine how many lags – the number of $\beta_i \Delta y_{t-i}$ terms – we include in our specification and testing. We add these lagged terms in order to correct for the presence of serial correlation in the error terms. Even if the null hypothesis is true, in other words we have a non-stationary series, we find that the estimators for the β terms have a t-distribution which allows us to test the significance of the β terms using t-tests or F-tests. If we add lag terms and find they are not significant, then they should not be included in the specification. In this way, the testing is a manually, iterative process to determine the correct number of lags to specify.

Another way in which to determine the number the number of lags is to continue adding them until the point at which we have no serial correlation in the error term ε_t .

The selection of lag length is an important practical issue. If the number of lags selected is too small, the remaining serial correlation in the errors will bias the test. If the lag length selected it too large, the power of the test will suffer. It is suggested that the inclusion of too many lags is the more “desirable” error to make. A paper by Ng and Perron (1995) suggests conducting an ADF test with a maximum number of lags. The absolute value of the t-statistic for the last lag is examined. If that value is greater than 1.6, then the maximum number of lags is determined. If the value is less than 1.6, the number of lags should be reduced by 1 and the process conducted again (Ng & Perron, 1995).

This iterative testing method will be applied to the data under review to determine the appropriate number of lags for the ADF test.

6.4.4.2 Phillips-Perron Unit Root Test

The Phillips-Perron Unit Root test is an alternative test to the ADF test in determining the whether a time series is stationary or not. Considering a stochastic time series model with the following form:

Equation 12

$$Y_t = \rho Y_{t-1} + \varepsilon_t$$

Where:

$$t = 1, 2, \dots, n$$

$$Y_0 = 0 \text{ and } \varepsilon_t = iid[0, \sigma^2]$$

The Phillips-Perron test makes use of a corrective form of the t-test to determine a value for ρ . This corrective form of the test corrects for the potential of serial correlation and heteroscedasticity in the error terms. Importantly, this corrective form of the test is non-parametric. Like the ADF test, the hypothesis is:

$$H_0: \rho = 1 \text{ (unit root, non-stationary)}$$

$$H_1: \rho < 1 \text{ (stationary)}$$

The Phillips-Perron test does not require the specification of the number of lags in the same way the ADF requires lag specification. This lack of lag specification requirement is because the corrective form of the t-test is robust to the presence of serial correlation and heteroskedasticity in the error terms. A comparison of the test statistic with a Phillips-Perron critical value is undertaken. If the test statistic is more negative (i.e. a lower value) than the Phillips-Perron critical value, then the null hypothesis is rejected. No unit root is present and the time series is stationary.

In work conducted in 2004, Davidson and MacKinnon determined that for small, finite samples, the ADF test outperformed the Phillips-Perron test. This finding, that it is best suited to large data samples, is the primary disadvantage of the Phillips-Perron test. However, given the dataset under review contains 40 to 50 thousand data points for each ETP instrument, the results of the Phillips-Perron test are unlikely to be affected by the problems addressed

by Davidson and MacKinnon (2004). In the interests of good practise to conduct multiple tests using varying approaches, the results of the Augmented Dickey-Fuller test and the Phillips-Perron test are discussed in 6.4.4.3 below.

6.4.4.3 Results of Testing for Nonstationarity

The Augmented Dickey-Fuller test and the Phillips-Perron test were conducted on the full date range of ETP range-based volatility. For each ETP, the range-based volatility measure for each 15-minute sample within the trading day was included in the data set. Data from the 6 May 2010, Flash Crash event, were excluded.

The ADF test results are presented in Appendix Section B.1. An analysis of the test statistics generated by the Augmented Dickey-Fuller test shows that for all ETP instruments, the test statistic was less negative (i.e. a higher value) than the ADF critical value. For all ETPs, we accept the null hypothesis that states that the series has a unit root and is non-stationary.

The choice of lag length for each ADF test pertaining to the various ETPs is also presented in the results. The methodology outlined in Section 6.4.4.1.2.1 is applied to the lag length selection process. The appropriate number of lags range from 17 for the ETP with ticker EWU to a lag length of 24 for a number of ETPs.

An analysis of the test statistics of the Phillips-Perron Test presents conflicting results for all but one ETP instrument. For the ETP with ticker EWQ, which is the iShares International ETP tracking the MSCI France index, the test statistic is greater than the Phillips-Perron critical value. This allows for the acceptance of the null hypothesis. The time series for EWQ has a unit root and is non-stationary. No discernible differences between the distributions characteristics of EWQ relative to the other ETP instruments under review can be readily identified. Further, more extensive examination is required to account for this result. For all other ETPs instruments tested, the test statistics are less than the Phillips-Perron critical values. We, therefore, reject the null hypothesis and conclude that no unit root is present and the time series are stationary.

6.4.4.3.1 Addressing the Conflicting Results

While somewhat dissatisfying to achieve conflicting results from the Augmented Dickey-Fuller test and the Phillips-Perron test, it is not unusual when analysing financial time series data. Kwiatkowski, et al. (1992) state that it is well-established that standard root tests fail to reject the null hypothesis for many economic time series. The conclusion that is typically asserted from an empirical analysis is that many economic time series contain a unit root. Kwiatkowski, et al. (1992) explain that in tests such as the Augmented Dickey-Fuller test and the Phillips-Perron test, the unit root is the null hypothesis being tested. Given the way in which classical hypothesis testing is conducted ensures the null hypothesis is accepted unless there is strong evidence against it (Kwiatkowski, et al., 1992). They suggest further that it is therefore useful to test the null hypothesis of stationarity as well as testing the null hypothesis of a unit root. To provide support for either the findings of the Augmented Dickey-Fuller test or the Phillips-Perron test, we introduce a third test of stationarity, the Kwiatkowski-Phillips-Schmidt-Shin test, hereafter referred to as the KPSS test.

6.4.4.4 The KPSS Test

The KPSS test is a stationary test – essentially opposite in hypothesis structure to the ADF and Phillips-Perron tests. Starting with the model specification below:

Equation 13

$$y_t = \beta' \mathbf{D}_t + \mu_t + u_t$$

Where:

$$\mu_t = \mu_{t-1} + \varepsilon_t, \varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$$

Where \mathbf{D}_t contains a constant, or a constant and a time trend and where $u_t = I(0)$. The hypothesis is given as:

$$H_0: \sigma_\varepsilon^2 = 0 \text{ (stationary)}$$

$$H_1: \sigma_\varepsilon^2 > 0 \text{ (non-stationary)}$$

The KPSS test is a one-sided, right-tailed test. The null of stationarity is rejected at the $100 \cdot \alpha\%$ level if the KPSS test statistic is greater than the $100 \cdot (1 - \alpha)\%$ quantile from the appropriate asymptotic distribution (Zivot, 2006).

The results of the KPSS test are presented in the Appendix Section B.3 and serve to support the findings of the Augmented Dickey-Fuller test, which accepted the null hypothesis of non-Stationarity of the range-based volatility measure for all ETP instruments. The KPSS test statistics are greater than the KPSS critical values, and we reject the null hypothesis of stationarity.

6.4.5 Conclusions from Stationarity Testing

As is often the case when conducting empirical analysis, and particularly when working with econometric or financial data series, the application of formal statistical testing can be a complex process. The results of the Phillips-Perron test conflict with the results obtained from the ADF test and the KPSS test. Schwert (1989) finds that if Δy_t can be described by an ARMA process and when that process contains a large and negative moving average component, then both the ADF test and the Phillips-Perron test may provide erroneous results. These errors would present as a rejection of the unit root null hypothesis too often when it is true. This is particularly true of the Phillips-Perron test (Schwert, 1989). Caner and Killian (2001) suggest that the KPSS test suffers from similar problems to the ADF and Phillips-Perron tests.

If we consider the data under review and make some intuitive comments, we should be unsurprised that the data appears to be non-stationary. During the period January 2006 to July 2014, financial markets experienced a major market and economic crisis. The Great Recession catalysed by the 2007/08 Credit Crisis undoubtedly resulted in a volatility profile which was different to the periods before and after the crisis. In order to determine whether this period in financial market history was accountable for the findings of non-stationarity, some preliminary testing was conducted. The ETP subset as identified in Section 6.3.1 was testing over a truncated date range to exclude the period from January 2007 to December 2008. The ADF test, Phillips-Perron test and KPSS test were conducted.

The results from this preliminary testing were mixed and inconclusive regarding the stationarity of the data series excluding the crisis period. Given the result ambiguity, and the desire to use a non-truncated dataset, the full date range from January 2006 to July 2014, excluding the Flash Crash event, will be used for additional analysis work.

6.5 Preparation for Statistical Analysis

We are attempting to determine whether those ETPs with underlying baskets that are listed in non-synchronous or partially synchronous markets to the ETP instrument exhibit a different volatility profile to ETPs with underlying baskets listed in synchronous markets to the ETP instrument itself. The volatility profile is measured by range-based volatility. We are now in a position to make informed choices on the statistical tests we will apply to evaluate and interpret the data.

Given our initial visual data analysis we exclude the data computed for 6 May 2010 in order to exclude the Flash Crash event. Although non-US baskets were less affected by the Flash Crash event, to ensure a consistent approach that date point is removed from all range-based volatility datasets.

The initial statistical analysis indicated two critical features of the data, namely:

1. The data are not normally distributed
2. The data are not stationary

The first feature can be addressed by ensuring that any statistical tests can provide accurate results for a non-normal dataset. Catering for non-normal data implies a selection of non-parametric testing processes. For the second feature, to make allowance for the non-stationarity of the data we must ensure that the statistical methods selected are not invalidated by this finding.

6.5.1 Non-Parametric Tests

Non-parametric tests are appropriate when no assumptions (i.e. normality) can be made about the underlying distribution of the data. Non-parametric tests are typically more robust than the equivalent parametric test, but non-parametric tests tend to have less statistical power and can often be more difficult to interpret.

The objective of this analysis is to determine whether there is a difference in volatility profile between non-synchronous, partially synchronous and synchronous ETPs. A statistical test is required that allows for the comparison of the median value of the range-based volatility measure of those ETPs with foreign underlying baskets, to the median value of the range-based volatility measure of the ETP which contains domestic, NYSE-listed securities as its underlying basket. Practically, that means comparing the median of each range-based volatility measure for ETP during every 15-minute time interval to the range-based volatility of the United States ETP with ticker IVV.

The two statistical tests typically used to compare the medians when the data are non-parametric are the Mann-Whitney U test and the Wilcoxon Signed Rank test.

6.5.1.1 Mann-Whitney U Test

The Mann-Whitney U test is a rank-based non-parametric test that can be used to determine if there are differences between two groups, either differences in the distributions of the two groups or differences in the medians of the two groups. It is often presented as an alternative to the t-test when normality assumptions fail or when the data are ordinal. To use the Mann-Whitney U test to determine whether there is a difference in medians between two groups, we need to need to meet the assumption that the distribution of the two groups is the same. The following general assumptions also need to be met:

1. One independent variable measured at the continuous or ordinal level.
2. One independent variable consisting of two categorical, independent groups.
3. Independence of observations – there is no relationship between the observations. (Laerd Statistics, n.d.)

Intuitively, the third general assumption is concerning given the financial data under review. Stock markets do not move independently of one another, and economic, geopolitical or other material sentiment drivers affect global markets. Yunus (2013) studied the dynamic interdependence between ten major markets over the period 1993 to 2008 using a recursive cointegration technique. Results indicated that international financial markets are integrated and bound together by four long-run relationships. The results also revealed that the United States contributes the most heavily to the common trends. This indicates the pre-eminent position of the United States as the global leader in that it leads and drives each of the other markets (Yunus, 2013).

As such, the likely violation of the third general assumption of the Mann-Whitney U indicates that the test is inappropriate for the purposes of this analysis.

6.5.1.2 Wilcoxon Signed Rank Test

The Wilcoxon Signed Rank test is a nonparametric test equivalent to the dependent t-test that does not rely on a normally distributed underlying dataset. It is typically used to compare two sets of results that come from the same dataset and carries the following general assumptions which need to be met in order to ensure statistical validity:

1. An independent variable that is measured at the continuous or ordinal level.
2. The independent variable should consist of two categorical, "related groups" or "matched pairs". "Related groups" typically

means the same subjects are present in both groups while “matched pairs” refers to different subjects.

3. The distribution of the differences between the two related groups needs to be symmetrical in shape.

Provided the range-based volatility data under review is able to satisfy the third required general assumption, the Wilcoxon Signed Rank test will provide an appropriate measure for answering the research question.

6.6 Statistical Analysis

6.6.1 Initial Statistical Analysis

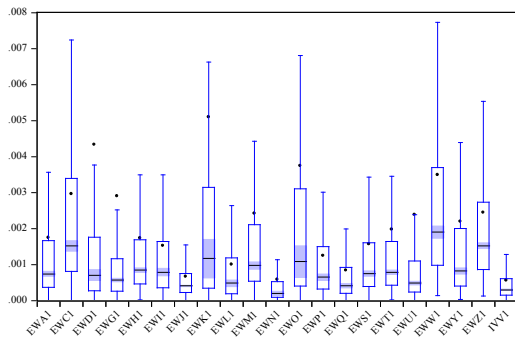
The objective of the statistical analysis is to compare the median value of each ETP’s range-based volatility measure in each 15-minute data interval to the median value of the ETP holding an underlying basket of stocks all listed in the United States. By comparing the medians of the non-synchronous, partially synchronous and synchronous ETP’s with that of the ETP tracking a basket of United States equities, we can begin to understand whether there is any persistence in range-based volatility characteristics of the ETP’s whose underlying baskets are in different time zones to the time zone of the instrument listing.

As a mechanism of the initial analysis, the charts below display range-based volatility measure for each ETP for each 15-minute intra-day time interval graphically displayed as a box plot. For the sake of clarity, we are comparing the median value of every ETP to the median value of the ETP with ticker IVV – the ETP tracking an underlying basket of United States equities.

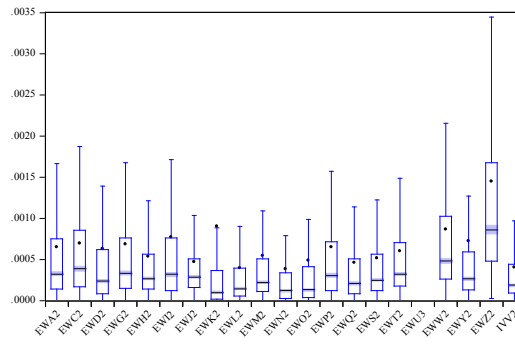
We therefore have 26 box plots reflecting the 26, 15-minute intraday intervals through the trading day. Note that the range-based volatility measure is determined from the open, high, low, close intraday price data over the time period the 1 January 2006 to the 11 July 2014. The data from the 6 May 2010 are excluded to remove the extreme effect of the Flash Crash.

Figure 6: Box Plot for All ETPs for Each 15-minute Intraday Interval

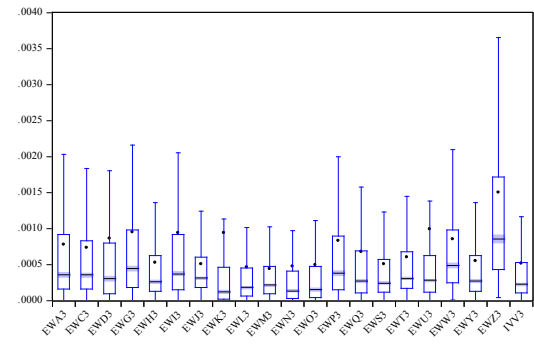
9.30am EST



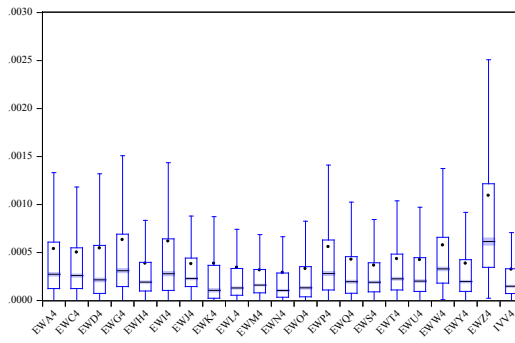
9.45am EST



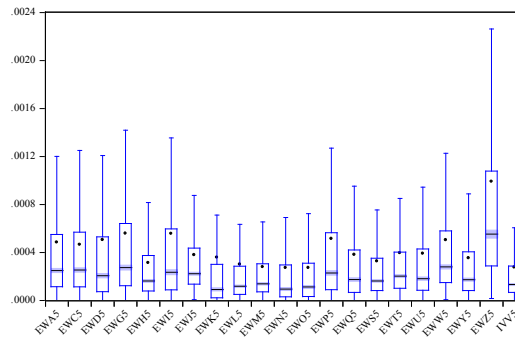
10.00am EST



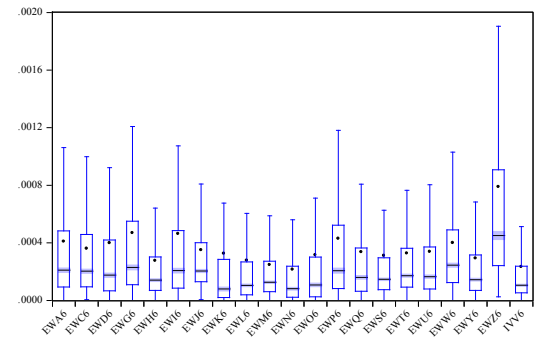
10.15am EST



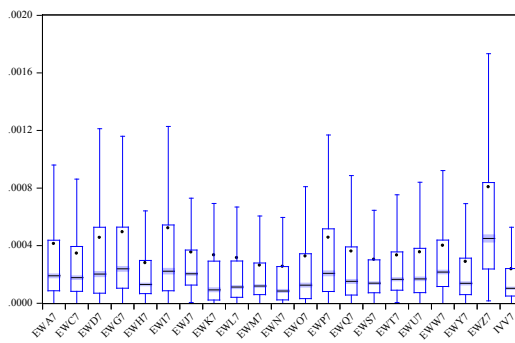
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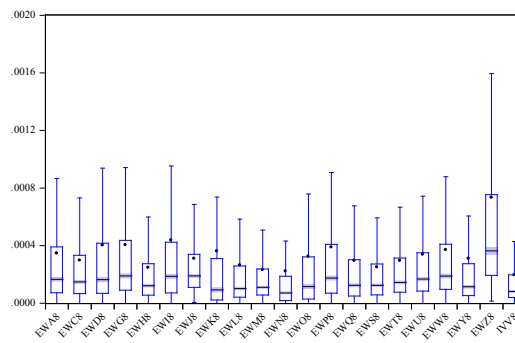
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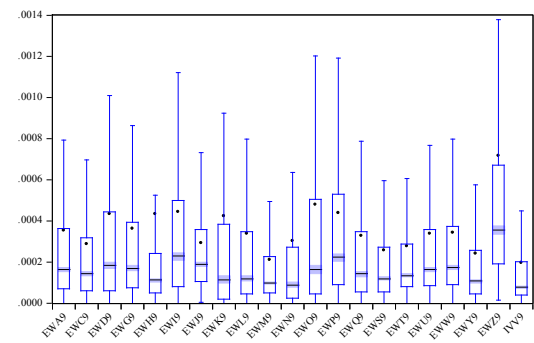
11.00am EST



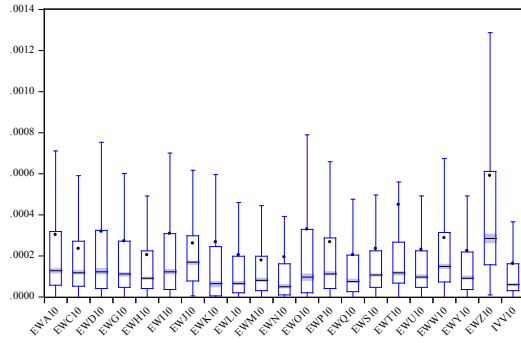
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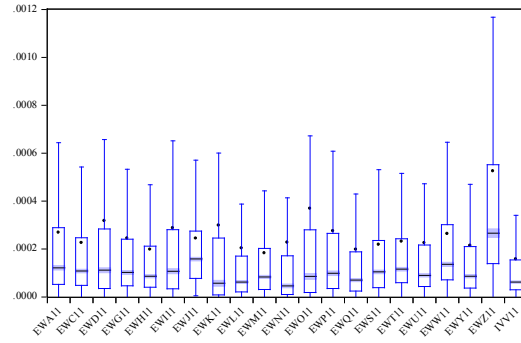
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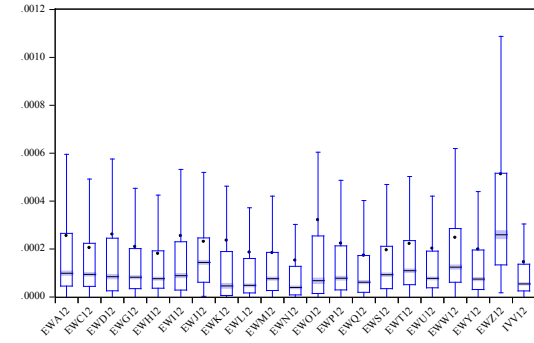
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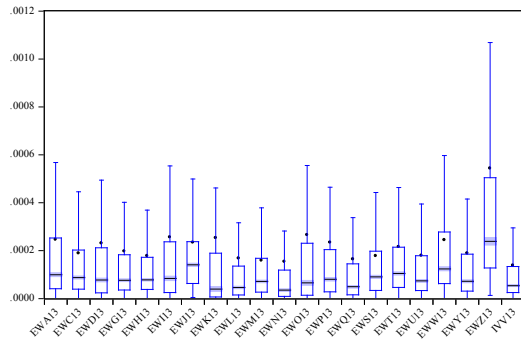
12.00 pm EST



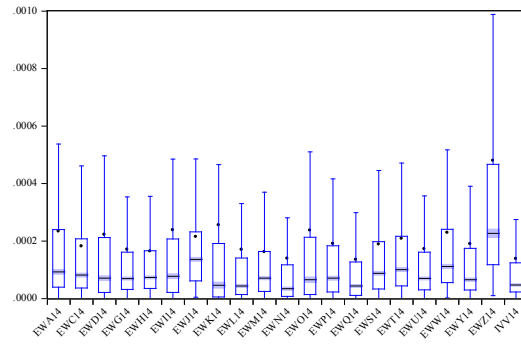
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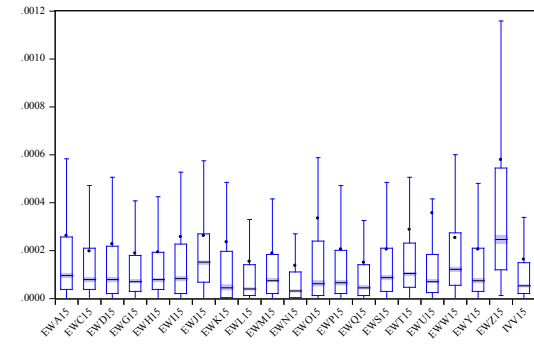
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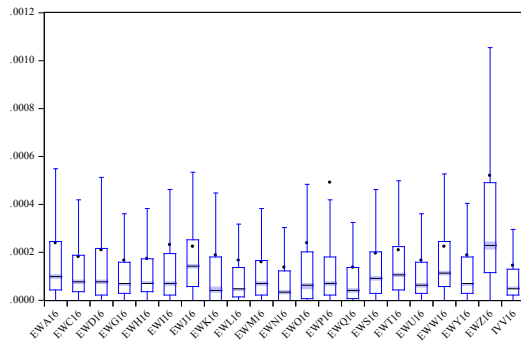
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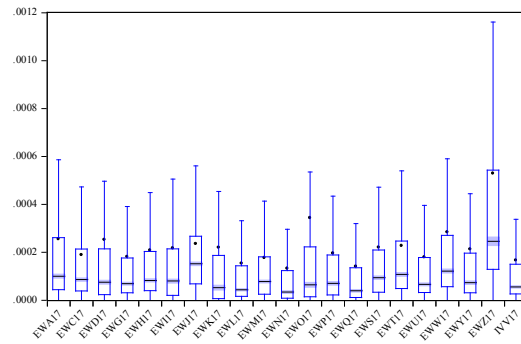
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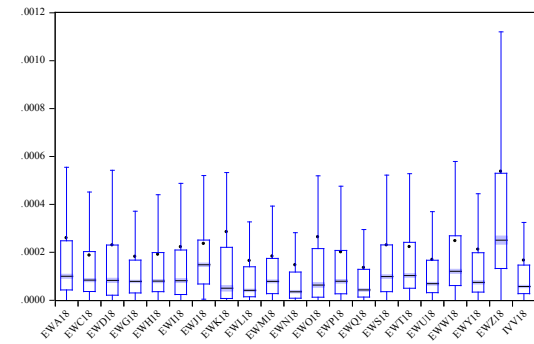
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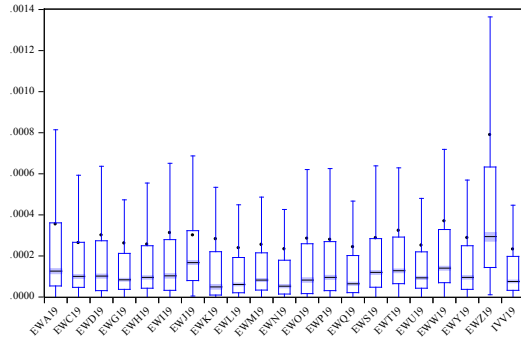
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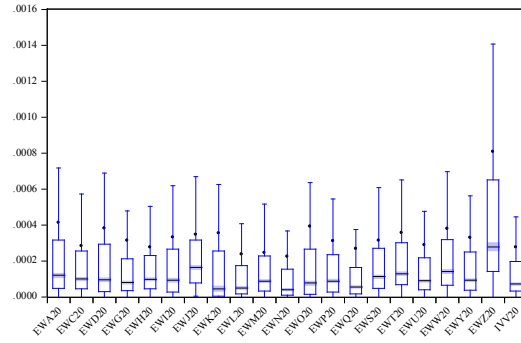
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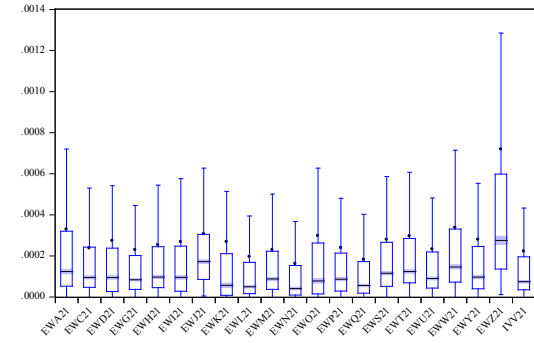
2.00pm EST



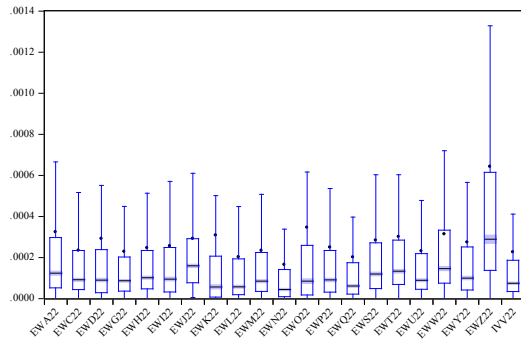
2.15pm EST



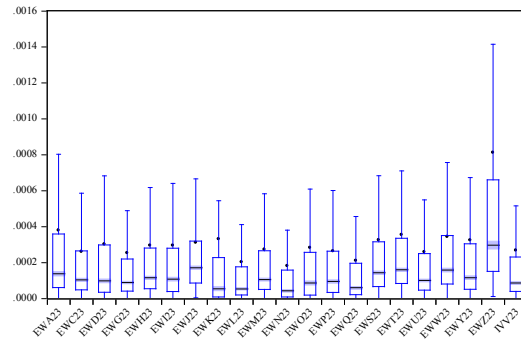
2.30pm EST



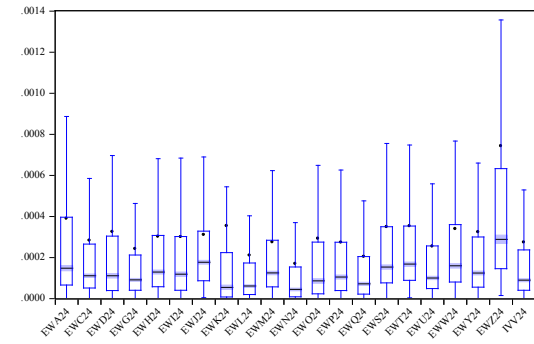
2.45pm EST



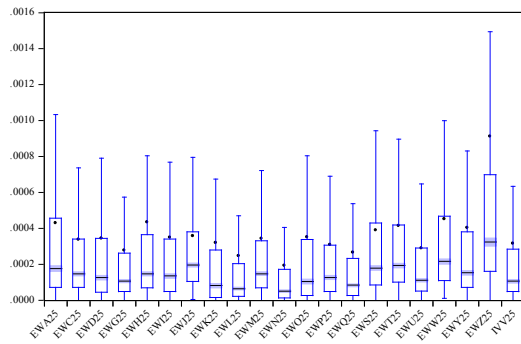
3.00pm EST



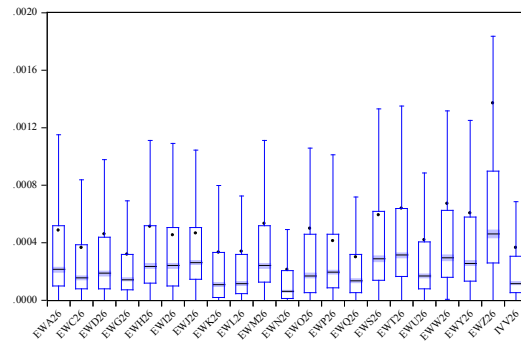
3.15pm EST



3.30pm EST



3.45pm EST



6.6.1.1 Preliminary Results from the Wilcoxon Signed Rank Test

Upon commencement of the computations of statistics for the Wilcoxon Signed Rank test, it became immediately evident that the third assumption of the test which states that the distribution of differences between the two time series needs to be symmetrical was violated. Voraprateep (2013) demonstrates that when the distribution changes from symmetry to asymmetry, the power of Wilcoxon signed-rank test decreases showing that the Wilcoxon signed-rank test is not applicable to an asymmetric distribution (Voraprateep, 2013). Given this violation, the available literature proposed two possible alternatives. The first alternative was to make use instead of the Sign test as opposed to the Wilcoxon Signed Rank test. The assumptions for the Sign test are provided below:

1. The dependent variable should be measured on a continuous (i.e., interval or ratio) or ordinal level.
2. The independent variable should consist of two categorical, "related groups" or "matched pairs".
3. The paired observations for each participant need to be independent. That is, one participant's values cannot influence another participant's values.
4. The difference scores (i.e., differences between the paired observations) are from a continuous distribution. (Laerd Statistics, n.d.)

Assumption 3 has a requirement for independence and given the rationale for selecting the Wilcoxon Signed Rank test rather than the Mann-Whitney U test, the Sign test will be inappropriate for the analysis of these data.

The second alternative is to transform the data in some way in order to adhere to the conditions of symmetry. Suggested transformations include an inverse or reciprocal transformation, taking the logarithm of the data (when the data are non-negative), taking the square root and other power transformations. As the data under review are non-negative and given that taking the natural logarithm of the data is a useful technique to reduce skewness in par-

ticular and therefore often used with financial data, the range-based volatility for each ETP for each 15-minute intraday time interval will be transformed by computing the natural logarithm. Under ideal conditions, the transformation of the data by taking the natural logarithm would normalise the distribution to the extent that parametric tests could be applied rather than non-parametric tests. Unfortunately, despite the transformation, the data remain non-normally distributed and as such, the non-parametric Wilcoxon Signed Rank test will be used.

6.6.1.2 Data Transformation and Test Specification

For each ETP as presented in the box plots above, the range-based volatility measure for each 15-minute intraday interval, was transformed by taking the natural logarithm of the range-based volatility measure. As the objective of this analysis is to determine whether there is a difference in volatility profile between non-synchronous, partially synchronous and synchronous ETPs, we compare the median value of the transformed range-based volatility measure for each 15-minute time interval of each ETP with a foreign underlying basket, to the median value of the transformed range-based volatility measure for of the ETP listed on the NYSE which contains NYSE-listed securities as its underlying basket, the ETP with ticker symbol IVV.

We carry out a test of the null hypothesis that the median of transformed, rang-based data of the foreign ETP is equal to the specified value of the median of the United States ETP against the two-sided alternative that it is not equal to the median of the United States ETP - IVV:

$$H_0: med(x) = m$$

$$H_1: med(x) \neq m$$

Where:

$$m = \text{median value of IVV}$$

The Eviews statistical software reports a *p-value* for the asymptotic normal approximation to the Wilcoxon t-statistic (correcting for both continuity and tied or numerically equal points). It is based on the premise of the Wil-

Wilcoxon Signed Rank test that if the absolute value of the difference between each observation and the median ranked from high to low is summed, the sum of the ranks above the median should be similar to the sum of the ranks below the median (Eviews 8 Users Guide I, 2014). Eviews also reports the number of observations above and below the specified median value as well as the mean rank. This provides a useful indication as to whether the tested median is above or below the specified median in the event that we reject the null hypothesis of the Wilcoxon Signed Rank test and accept the alternative.

Full details of the results of the Wilcoxon Signed Rank test are provided in the supporting documentation. A summary of the findings will be discussed below.

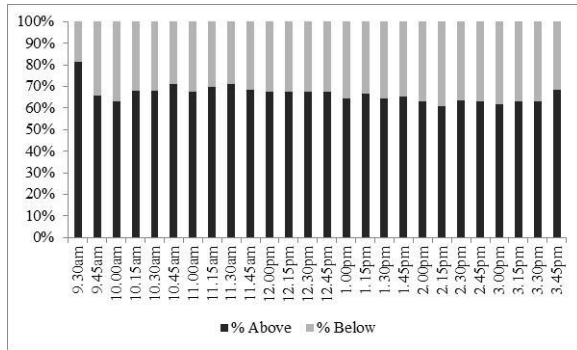
6.6.2 Results of the Wilcoxon Signed Rank Test

The results of the Wilcoxon Signed Rank test were unanimous and unambiguous across all ETPs and for each 15-minute intraday period. No ETP exhibited a median that was statistically equivalent to the median of the ETP tracking the underlying basket of stocks listed in the United States with ticker IVV. For all ETPs and for each intraday time interval, we reject the null hypothesis of equal medians and accept the alternative hypothesis of non-equal medians.

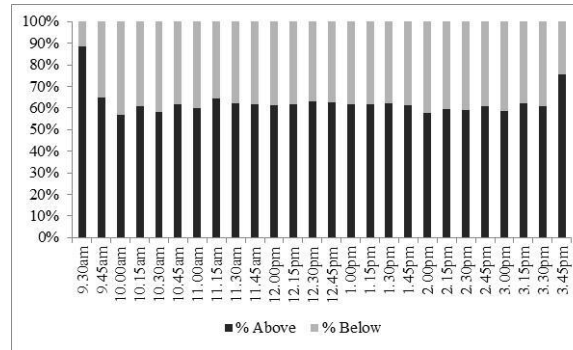
For each ETP and for each 15-minute intraday interval over the data range, we are able to identify how many observations fall above the median of the United State ETP and how many observations fall below the median of the United States ETP. Given the total number of observations, we can determine on a percentage basis, how many observation fall above the United States ETP median and how many below. These observations were then plotted graphically and can be found below separated into non-synchronous, partially synchronous and synchronous groups.

Figure 7: Non-synchronous ETPs - Percentage Observations Above and Below United States ETP Median

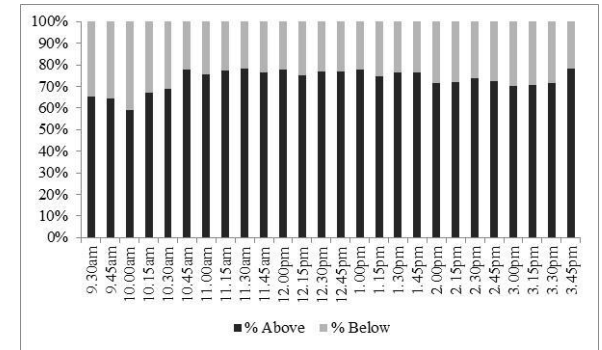
EWA – Australia



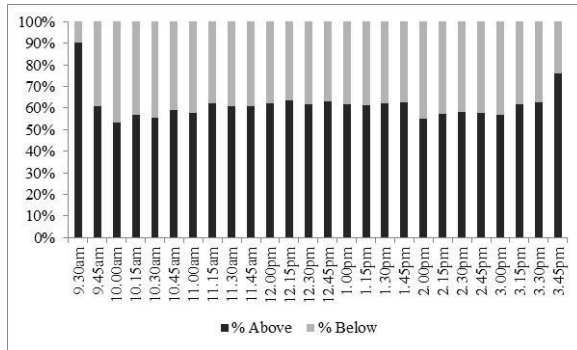
EWH – Hong Kong



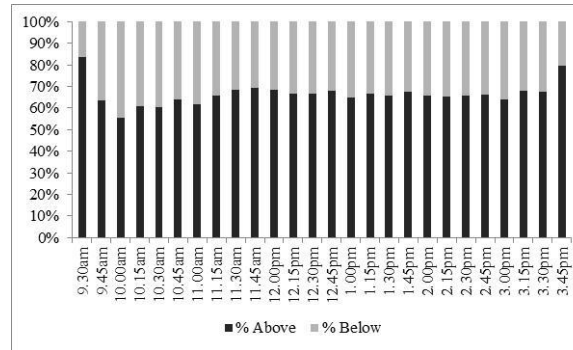
EWJ – Japan



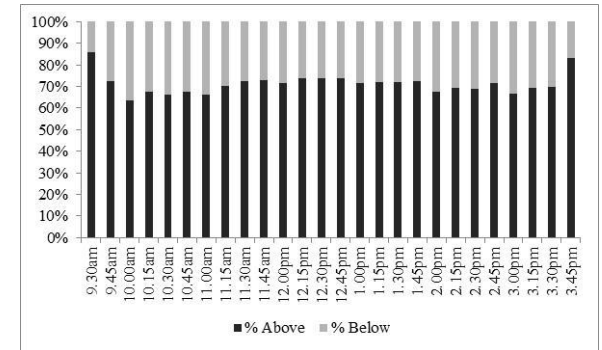
EWM – Malaysia



EWS – Singapore



EWT – Taiwan



EWY – South Korea

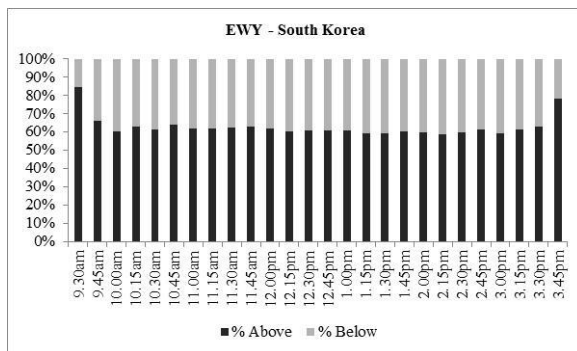
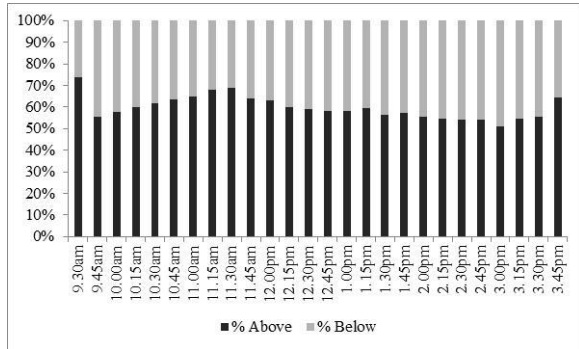
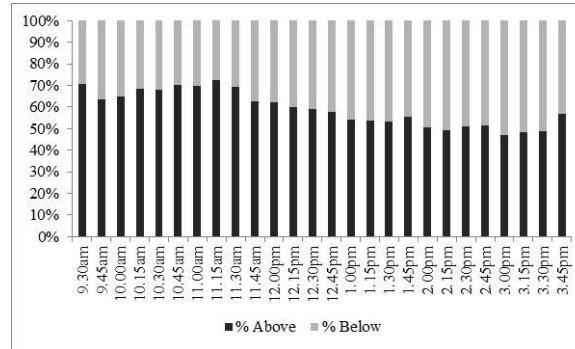


Figure 8: Partially synchronous ETPs - Percentage Observations Above and Below United States ETP Median

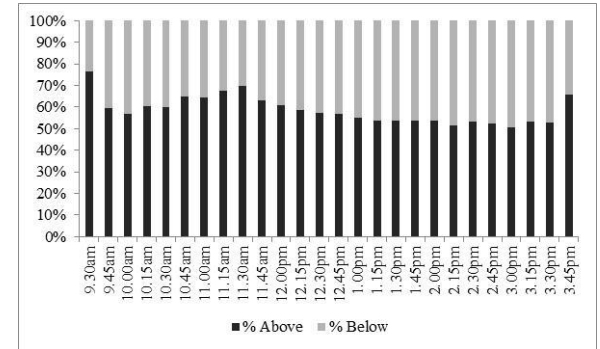
EWD – Sweden



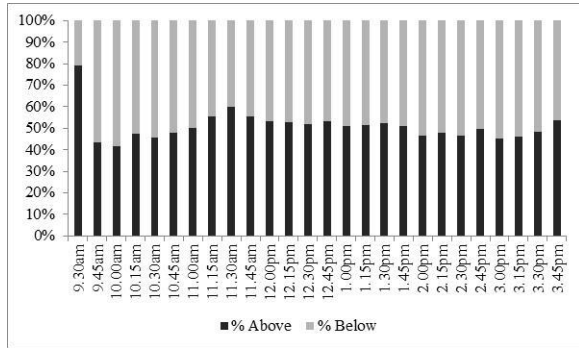
EWG – Germany



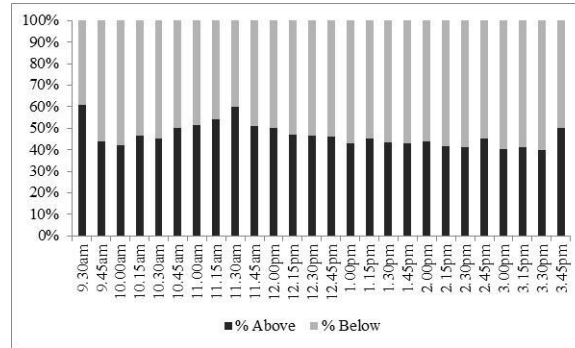
EWI – Italy



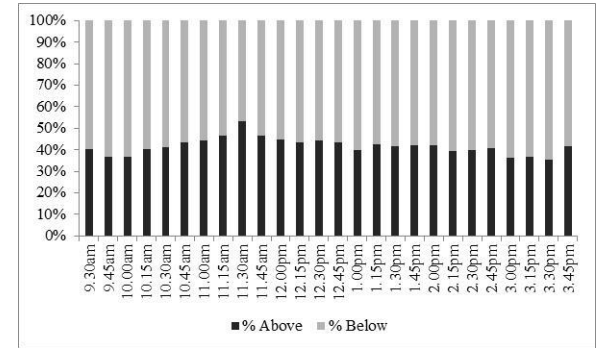
EWK – Belgium



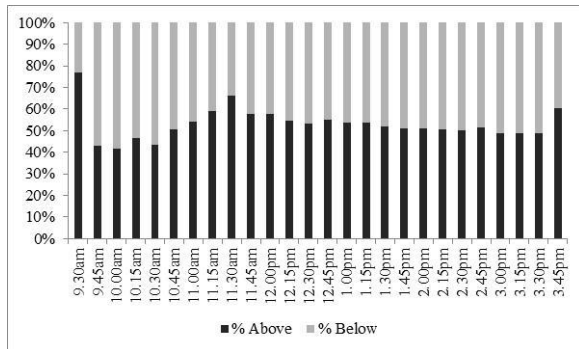
EWL – Switzerland



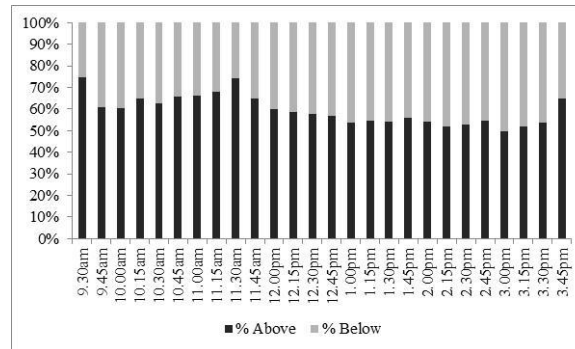
EWN – Netherlands



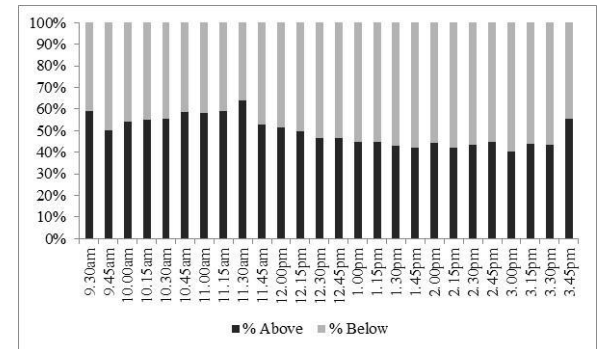
EWO – Austria



EWP – Spain



EWQ – France



EWU – United Kingdom

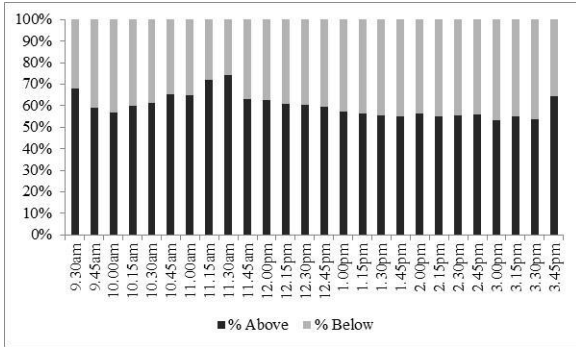
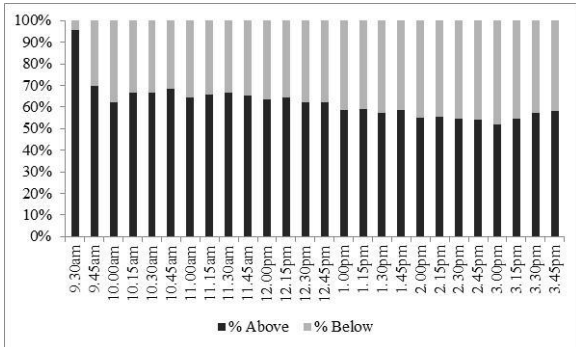
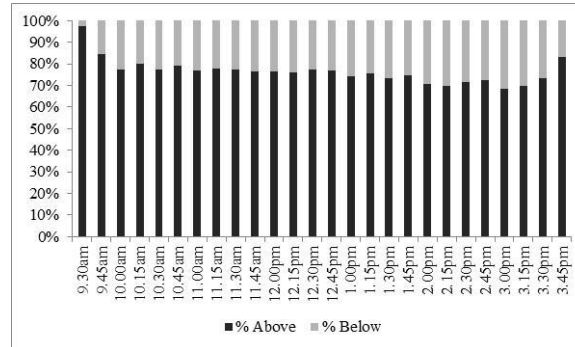


Figure 9: Synchronous ETPs - Percentage Observations Above and Below United States ETP Median

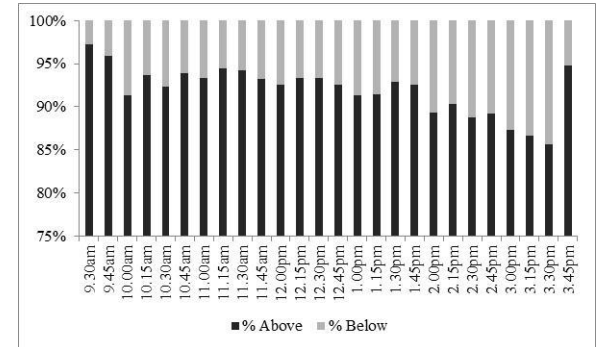
EWV – Canada



EWW – Mexico



EWZ – Brazil



6.6.2.1 Discussion of Wilcoxon Signed Rank Test Results

The graphical results provide some interesting qualitative insights and suggest avenues for further interrogation and research. Additionally, an average is presented both for each ETP where the average for the individual ETPs is given as:

Equation 14

$$\text{Ave \% Above IVV} = \frac{\sum_{i=1}^n Ppos_i}{n}$$

Equation 15

$$\text{Ave \% Below IVV} = \frac{\sum_{i=1}^n Pneg_i}{n}$$

Where:

$Ppos_i$ = % observations above IVV median for time interval i

$Pneg_i$ = % observations below IVV median for time interval i

n = number of 15 minute intraday intervals

In addition to computing a simple average for each individual ETP across the 26 intraday, 15-minute time intervals, a simple average for the non-synchronous, partially synchronous and synchronous groups is also presented. These statistics form the basis of a qualitative or observational discussion presented below.

Table 4: Average Percentages Above and Below IVV Median per ETP

	Ave % Above IVV Median	Ave % Below IVV Median
Non-Synchronous ETP	66.35%	33.65%
Group Average		
EWA – Australia	66.60%	33.40%
EWB – Hong Kong	62.63%	37.37%
EWJ – Japan	73.19%	26.81%
EWM – Malaysia	61.57%	38.43%
EWS – Singapore	66.54%	33.46%
EWT – Taiwan	71.20%	28.80%
EWY – South Korea	62.69%	37.31%

Partially Synchronous ETP	53.94%	46.06%
Group Average		
EWD – Sweden	59.76%	40.24%
EWG – Germany	59.20%	40.80%
EWI – Italy	58.68%	41.32%
EWK – Belgium	51.06%	48.94%
EWL – Switzerland	46.60%	53.40%
EWN – Netherlands	41.67%	58.33%
EWO – Austria	53.08%	46.92%
EWP – Spain	59.52%	40.48%
EWQ – France	49.74%	50.26%
EWU – United Kingdom	60.06%	39.94%
Synchronous ETP	76.88%	23.12%
Group Average		
EWC – Canada	62.23%	37.77%
EWV – Mexico	76.43%	23.57%
EWZ – Brazil	91.99%	8.01%

6.6.2.1.1 Non-Synchronous ETP Group

The non-synchronous ETPs, in other words, those ETPs which have underlying stock baskets that trade on exchanges with no overlapping market hours with the New York Stock Exchange show levels of range-based volatility that are persistently higher than the equivalent range-based volatility measure for the United States ETP with ticker IVV. Examining the average percentages above and below the ETP median, we observe that Japan and Taiwan tend to exhibit more observations above the IVV median than do the other members of the non-synchronous group. The average for the group shows that two-thirds of group observations are higher than the equivalent IVV median.

An examination of the associated graphical representation indicates that the opening and closing 15-minutes of the New York trading day show levels of range-based volatility for the non-synchronous group as being observationally higher than the equivalent IVV measure 83% and 77% of the time respectively.

6.6.2.2 Partially Synchronous ETP Group

The partially synchronous group offers some interesting observations. In contrast to the non-synchronous group, the ETPs with underlying baskets rep-

representing the markets of Switzerland, the Netherland and France, show their percentage observations above the IVV median to be less than 50%. Observationally, this implies the range-based volatility of these ETPs tends to be less than the equivalent range-based volatility measure of IVV. And, also in contrast to the non-synchronous group, only the ETP with a United Kingdom underlying basket displays observations above the median of IVV 60% or more of observations.

As a group, the partially synchronous ETPs display a tendency to have a lower number of observations greater than or above the equivalent IVV observation relative to their non-synchronous counterparts.

Through a visual examination of the graphical output, it can be observed that apart from the first 15-minute time interval of the New York trading day when as a group, 68% of observations are above the equivalent IVV median, the time intervals from 11:15am to 11:30am and from 11:30am to 11:45am show a higher percentage of observation above the IVV median than any other 15-minute intraday interval with percentage observations above the median ranging between 62% and 66% respectively. The closing 15-minute interval for the group shows 58% of observations above the IVV equivalent.

Upon review the information contained in Figure 2, we note that the Italian market closes first at 11:25am, followed by France, Spain, Switzerland, Sweden and the United Kingdom at 11:30am, Austria at 11:35am and Belgium and the Netherlands at 11:40am. The German market is unique as it remains open for trading through to the New York market close at 4:00pm.

Intuitively, it appears from these observations that the close of the partially synchronous markets midway through the trading day is impacting on the range-based volatility measure of these ETPs. It is an area for further investigation and analysis.

6.6.2.3 Synchronous ETP Group

The Synchronous ETP group also offers interesting observations. A logical assumption might be that as the underlying markets are open during the New York trading day, there could be more certainty in the establishment and

verification of the ETP NAV – the valuation of the underlying basket – leading to less uncertainty in the pricing of the ETP instrument and hence a lower measure of range-based volatility. Under these circumstances, we could expect the median levels of Canadian, Mexican and Brazilian ETPs to show a closer alignment to the median levels of the United States ETP. The findings are, however, contrary to this assumption.

All three synchronous ETPs show a higher percentage of observations above the IVV median value and the ETP tracking an underlying basket of Brazilian stocks exhibits the highest percentage observations above the IVV median with a value of 92%.

There would appear to be another factor at work driving the range-based volatility measures. The obvious candidate for this disparity is currency influences. While the ETP instruments themselves are listed on the New York Stock Exchange and priced in United States Dollars, the underlying basket of stocks are priced in their respective local currencies and then translated into United States Dollars at the prevailing exchange rate to establish a US Dollar based Net Asset Value.

6.6.2.4 Additional Areas of Investigation

Following on from the results and qualitative interpretation above, two findings will be investigated more thoroughly. The first is an analysis of the apparent effect on the range-based volatility of the partially synchronous group during the intervals which encompass the closing of their respective underlying markets.

The second area of investigation will be an analysis of the role that foreign exchange plays in the results obtained.

Chapter 7

7 Partially Synchronous ETPs

7.1 European Market Closing

As discussed in 6.6.2.2, the closing of the partially synchronous or European markets mid-morning during the United States trading day appears to have some effect on the range-based volatility measure of those ETPs with European underlying baskets. This perceived effect will be tested more closely.

Again, making use of the Wilcoxon Signed Rank Test as outlined in 6.5.1.2, an analysis of the median value of the range-based volatility measure of each partially synchronous ETP will be tested in two ways. As observed in 6.6.2.2, the time intervals from 11:15am to 11:30am and from 11:30am to 11:45am show a higher percentage of observations above the IVV median. Instead of comparing the median value of the foreign ETP to the median value of the United States ETP, the median value for each foreign ETP in the 15-minute time interval from 11:00am to 11:15am will firstly be compared to the median value for that same ETP in the 15-minute time interval from 11:15am to 11:30am. Secondly, the median value in the 15-minute time interval from 11:30am to 11:45am will be compared to the median value of the same ETP in the 15-minute time interval from 11:45am to 12:00pm. By conducting and assessing the results of these two tests, some insight will be gained into whether the range-based volatility is different during the European market closing interval than in the 15-minute intervals immediately preceding and following the close.

Again, in order to comply with the assumptions of the Wilcoxon Signed Rank Test, transformed data will be used, where the natural logarithm of the

range-based volatility measure will be tested rather than the underlying range-based volatility measure itself.

The Wilcoxon Signed Rank Tests are specified as follows:

$$H_0: med(x) = m$$

$$H_1: med(x) \neq m$$

Where:

$$m = \text{median value of interval } 11:00\text{am to } 11:15\text{am}$$

$$H_0: med(x) = m$$

$$H_1: med(x) \neq m$$

Where:

$$m = \text{median value of interval } 11:45\text{am to } 12:00\text{pm}$$

7.1.1 Results of the Wilcoxon Signed Rank Test – Partially synchronous ETPs

The test statistics are presented in full in Appendix C, but are discussed below. In comparing the median value of each ETP in the time interval 11:00am to 11:15am to the median value of that same ETP in the time interval from 11:15am to 11:30am, we find that for three of the ETPs, we can accept the null hypothesis of equal medians.

For the ETP with ticker EWU tracking the United Kingdom underlying stock basket, the ETP with ticker EWO tracking the Austrian underlying stock basket and for the ETP with ticker EWK tracking the Belgium underlying stock basket, we find Wilcoxon Signed Rank test statistics of 0.199 ($p\text{-value} = 0.84$) and 2.48 ($p\text{-value} = 0.013$) and 1.08 ($p\text{-value} = 0.28$) respectively. The median values are not statistically different in the first 15-minute time interval to the second 15-minute time interval for these three ETPs. For the remaining ETPs in the partially synchronous basket, we reject the null hypothesis and find that the median values in the first 15-minute time interval are different to the median values in the second 15-minute time interval.

In comparing the median value of each ETP in the time interval 11:30am to 11:45am to the median value of that same ETP in the time interval from

11:45am to 12:00pm, we find that for all of the ETPs in the partially synchronous basket, we reject the null hypothesis. The median values in the time period 11:30am to 11:45am are statistically different to the median values in the time period 11:45am to 12:00pm.

Again, the Wilcoxon Signed Rank test statistic does not provide an indication of the direction or magnitude of the difference in median values, and so for the purposes of qualitative discussion, the percentage observations above and below the median are presented.

Table 5: Percent Observations Above and Below Median Value in Interval 11:00am to 11:15am Compared with Median in Interval 11:15am to 11:30am for Partially Synchronous ETPs

	% Above	% Below
	Median	Median
EWD – Sweden	46.53%	52.84%
EWG – Germany	48.56%	51.14%
EWI – Italy	45.38%	54.08%
EWK – Belgium	47.10%	53.14%
EWL – Switzerland	47.64%	52.17%
EWN – Netherlands	46.48%	53.11%
EWO – Austria	46.73%	53.31%
EWP – Spain	46.60%	52.79%
EWQ – France	45.26%	53.69%
EWU – United Kingdom	50.53%	49.53%

Table 6: Percent Observations Above and Below Median Value in Interval 11:30am to 11:45am Compared with Median in Interval 11:45am to 12:00pm for Partially Synchronous ETPs

	% Above	% Below
	Median	Median
EWD – Sweden	49.84%	50.28%
EWG – Germany	54.33%	42.90%
EWI – Italy	50.99%	48.44%
EWK – Belgium	50.80%	48.98%
EWL – Switzerland	53.30%	44.31%
EWN – Netherlands	49.59%	50.75%
EWO – Austria	50.56%	49.15%
EWP – Spain	52.71%	44.43%
EWQ – France	52.03%	46.16%
EWU – United Kingdom	54.26%	41.79%

The 15-minute time interval from 11:00am to 11:15am is just prior to the start of the closing period for those European markets which close from 11:25am (Italy), 11:30am (France, Spain, Switzerland, Sweden and the United Kingdom), 11:35am (Austria) and 11:40am (Belgium and the Netherlands). The German market remains open through the New York trading day. The time interval from 11:45am to 12:00pm is therefore just after the close of all European markets apart from Germany.

If European markets do exhibit higher range-based volatility during the closing interval, it could be expected that when comparing the interval just prior to the close, i.e. 11:00am to 11:15am, a lower level of range-based volatility could be observed relative to the closing interval of 11:15am to 11:30am. It could then also be expected that the range-based volatility in the interval 11:30am to 11:45am which falls within the closing period would be higher than the range-based volatility in the interval 11:45am to 12:00pm.

Using the data presented in Table 5, we note that apart from the United Kingdom, there are slightly more observations below the median value than above. This supports the notion that the range-based volatility in the interval just prior to the start of the European market close tends to be lower than during the closing period.

Using the data presented in Table 6 we observe that apart from Sweden and the Netherlands, more observations in the closing period interval 11:30am to 11:45am fall above the median value of the interval 11:45am to 12:00pm which is just after all European markets apart from Germany have closed. This suggests a tendency for range-based volatility to be higher in the closing interval than in the subsequent intervals.

7.1.2 Discussion on Increased Volatility

In referring to Section 3.2.2 and Section 3.2.3, we discussed literature from Levy and Lieberman (2013) whose dataset closely matches that used in this paper. They examined the iShares MSCI Country Series of ETPs and used 15-minute intraday data for their analysis. Their study found that when domestic markets are open, ETP returns are driven predominantly by NAV returns,

in other words, the pricing of the underlying securities listed on the domestic market. They then found that when the underlying domestic market closed, the ETP returns were dominated by the returns of the S&P 500. They determined that there was a “regime shift” which occurred for European ETPs with the effect of the S&P 500 on European ETP pricing increasing significantly after the European market close.

It would appear that as the “regime shift” occurs, and the S&P 500 begins to denominate the pricing of the European ETPs as proposed by Levy and Lieberman (2013), the lack of pricing certainty and transition to new pricing driver, is reflected in higher volatility for the ETP instruments.

As per the intraday pricing mechanism discussed in 2.2.5, we recall that an indicative NAV is provided for intraday ETP pricing. This iNAV translates the prices of the underlying basket of securities at the prevailing currency rate of the listed ETP instrument. Given we have a situation in the European markets where, during overlapping market hours, the iNAV has a high degree of accuracy as the underlying basket of securities is “live”, and then becomes stale as the European markets close, a degree of discontinuity at the close is to be expected.

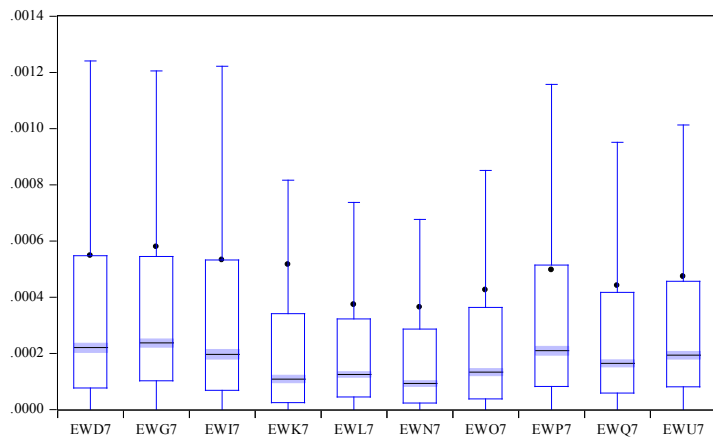
In Section 2.3.3, it was stated that international securities traded in different time zones or securities priced in multiple currencies all increase the complexity of the NAV calculation. APs may find it more difficult and expensive to create the underlying security basket for an in-kind creation or redemption. The arbitrage mechanism is, therefore, less efficient.

A pricing regime shift, a less transparent and more complex iNAV computation and a diminished ability for APs to undertake arbitrage are all factors which point to pricing uncertainty and increased volatility as the impact of the European market close is transmitted through the partially synchronous ETP group.

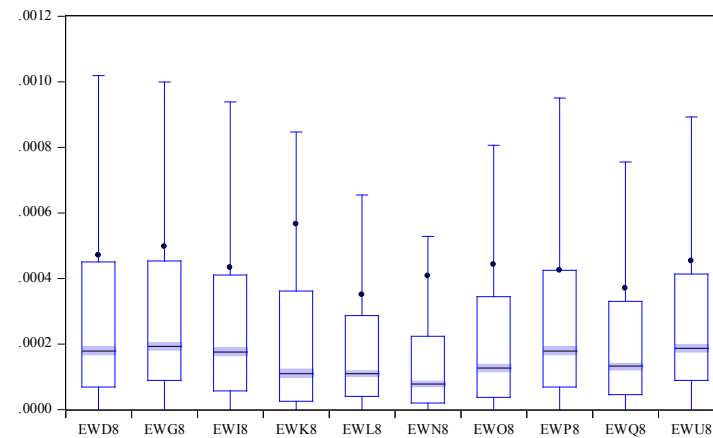
From a practitioner’s perspective, increased volatility in prices for the partially synchronous group suggests far greater care needs to be applied when transacting in these instruments during this transition period during the US trading day.

Figure 10: Range-based Volatility of Partially Synchronous ETPs Before, During and After European Market Close

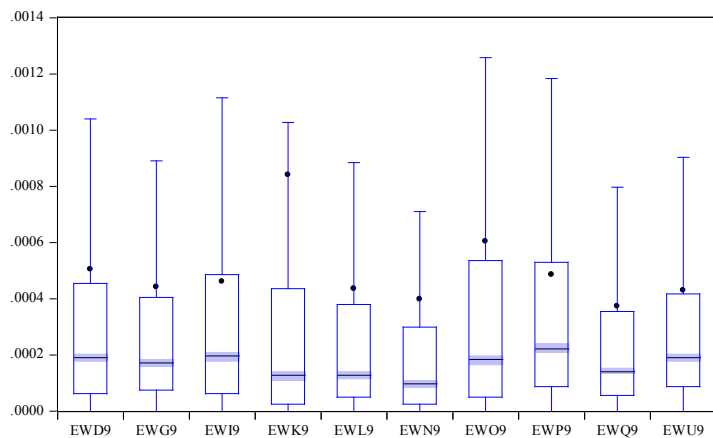
Time Interval from 11:00am to 11:15am (Before Close)



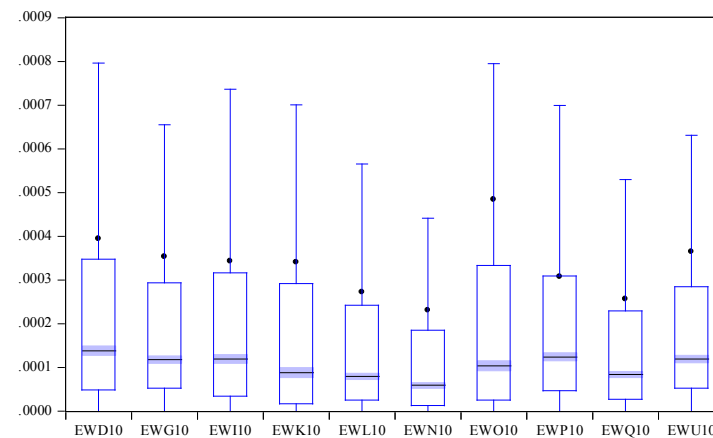
Time Interval from 11:15am to 11:30am (During Close)



Time Interval from 11:30am to 11:45am (During Close)



Time Interval from 11:45am to 12:00pm (After Close)



Chapter 8

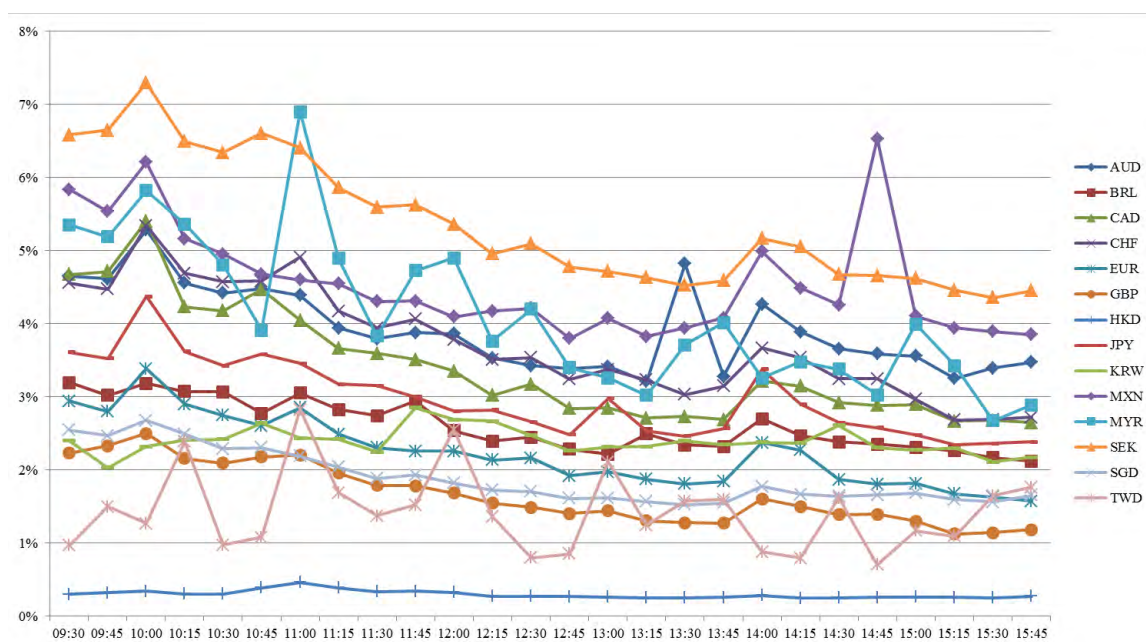
8 The Impact of Foreign Exchange

8.1 Range-based Volatility Computations

The foreign exchange data gathered comprises of 15-minute intraday open, high, low and close prices for the date range 28 September 2009 to 11 July 2014. A description of these data can be found in Table 2.

Although this paper does not focus on the intraday volatility displayed in foreign exchange markets, in order provide some consistency with the analysis work conducted on the ETP instruments, a range-based volatility for each foreign exchange instrument is computed based on the methodology proposed by the Yang-Zhang-Garman-Klaas extension presented in Equation 4.

Figure 11: Range-based Volatility Measure of Foreign Exchange Pairs - Sep 2009 to Jul 2014



As with the ETP data presented in Figure 4, a persistent intraday pattern in the foreign exchange intraday volatility can be observed. Unlike the pattern seen in the ETPs which showed a typical U-shaped intraday pattern with volatility higher at the open and close and tapered during the mid-part of the trading day, the range-based volatility for the selected foreign exchange pairs tends to show a downward trend in volatility over the course of the US trading session. Greater investigation beyond the scope of this work is required to provide a detailed explanation of the mechanisms at work in the forex market that could account for this volatility profile.

Observationally, we note that the Hong Kong Dollar (HKD) exhibits the lowest level of intraday volatility versus the United States Dollar (USD). The New Taiwan Dollar (TWD) also exhibits low intraday volatility although with a far more variable profile than the HKD. The HKD is a pegged currency meaning the Hong Kong Monetary Authority manages the exchange rate versus the USD between a tight floor and ceiling rate. The currency is not allowed to float freely on the open market and price according to free-market demand and supply interactions. The TWD is not explicitly pegged but is a managed float. The Central Bank of China takes responsibility for the management of Taiwan's currency and regularly intervenes in the currency market to smooth volatility (Shamah, 2011).

It was anticipated that, aside from pegged and managed float currencies, there would be clearer evidence of a volatility profile difference between developed market currencies (Australia, Canada, Eurozone, Hong Kong, Japan, Singapore, Sweden, Switzerland and Great Britain) and those from emerging market countries (Brazil, Malaysia, Mexico, South Korea and Taiwan) as defined by the MSCI Country Classification Standard (MSCI Inc, 2014). Upon visual inspection, no discernible difference is observed. The Swedish Krona displays the highest level of intraday range-based volatility against the USD with the Great British Pound displaying the lowest level of volatility of the free float currency pairs.

8.2 Local Currency ETP Prices

In order to examine whether the volatility difference observed between the non-synchronous, partially synchronous and synchronous ETPs is a function of currency in addition to, or perhaps instead of, time zone, the price data for the ETP instruments was converted back into the base currency of the underlying security baskets.

As the equivalent 15-minute intraday data for the foreign exchange pairs versus the USD was sourced from 28 September 2009, the converted price data will be analysed from this later date rather than 1 January 2006.

As it is impossible to determine from the data set the exact rate at which to convert the ETP open, high, low and close prices, an appropriate spot rate must be selected for each 15-minute interval. In order to simplify the translation process, a mid-price defined as the average between the open and close price for each 15-minute interval will be used to translate the open, high, low and close prices of the USD ETP prices into the ETP base currency.

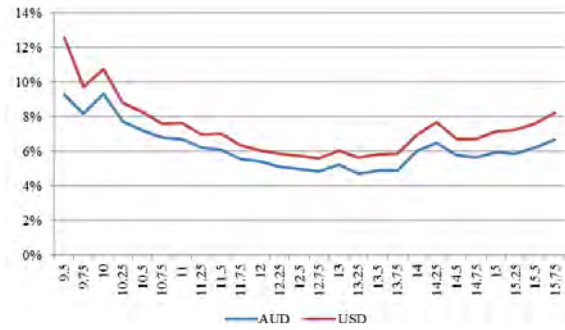
Upon conversion, the range-based volatility is computed to determine the intraday volatility profile of the translated ETP instrument.

8.3 Intraday Volatility Profile in Currency of Underlying Basket

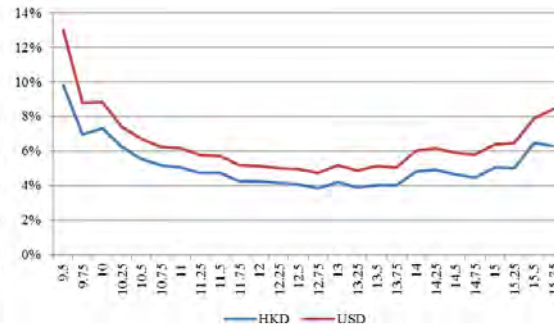
The Yang-Zhang-Garman-Klaas extension presented in Equation 4 is used to determine an intraday volatility profile for each ETP instrument after translation into the currency of the underlying basket. The intraday volatility profile of the instrument in USD is compared with the intraday volatility profile of the translated instrument. This is presented graphically below.

Figure 12: Non-Synchronous ETP Range-based Volatility - USD versus Underlying Currency - Sep 2009 to Jul 2014

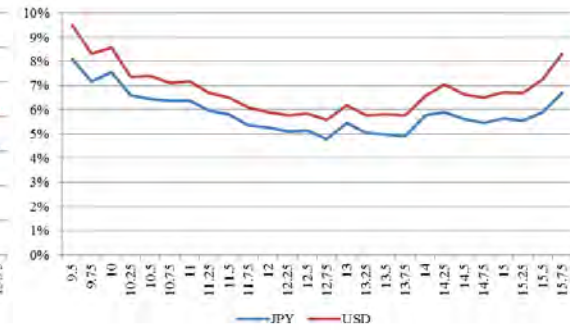
EWA – Australia



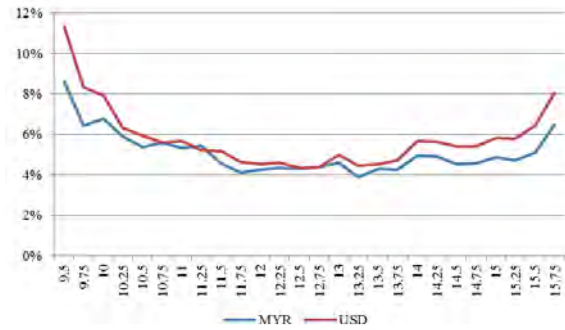
EWB – Hong Kong



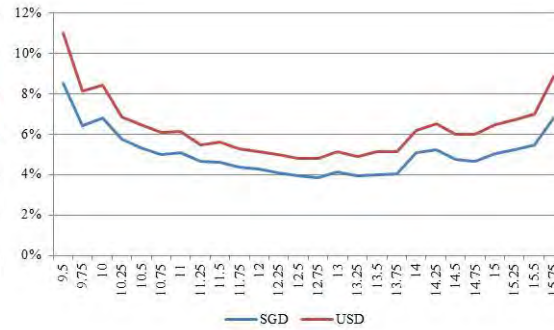
EWJ – Japan



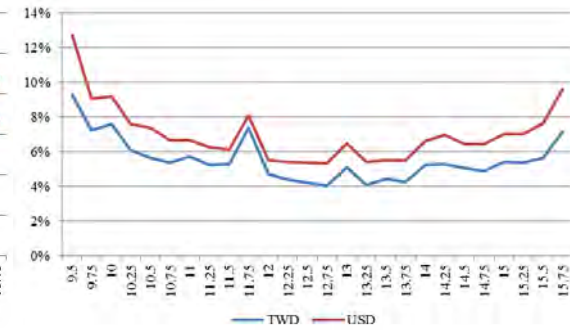
EWM – Malaysia



EWS – Singapore



EWT – Taiwan



EWY – South Korea

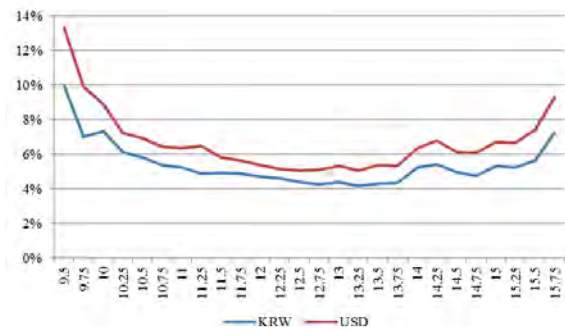
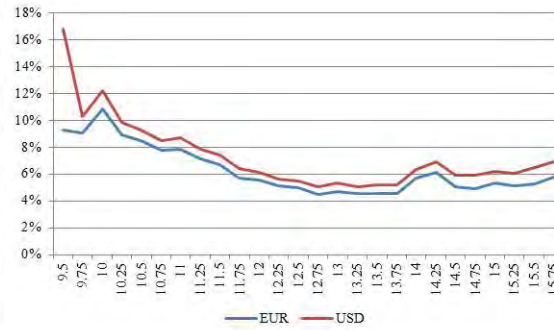


Figure 13: Partially Synchronous ETP Range-based Volatility - USD versus Underlying Currency - Sep 2009 to Jul 2014

EWD – Sweden



EWG – Germany



EWI – Italy



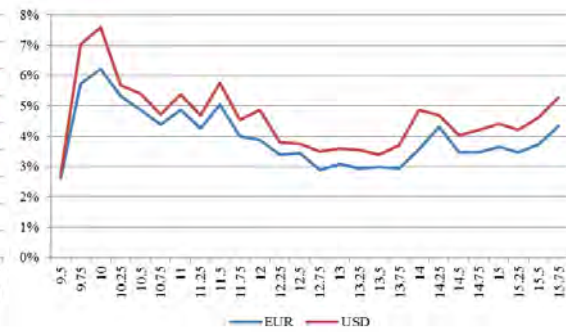
EWK – Belgium



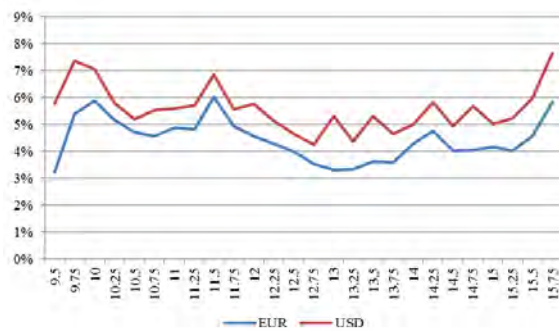
EWL – Switzerland



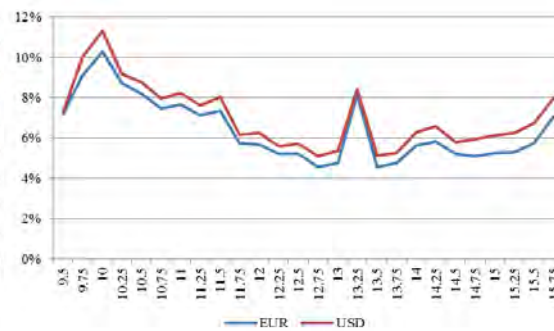
EWN – Netherlands



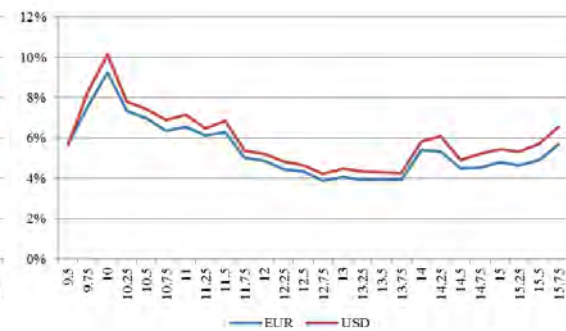
EWO – Austria



EWP – Spain



EWQ – France



EWU – United Kingdom

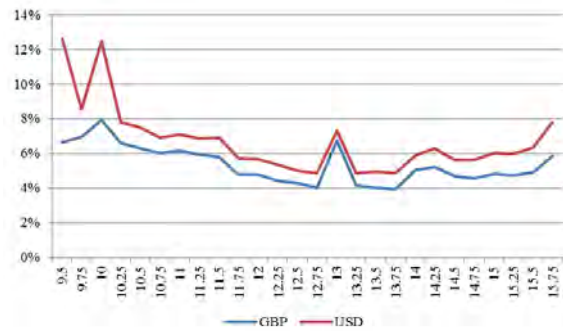
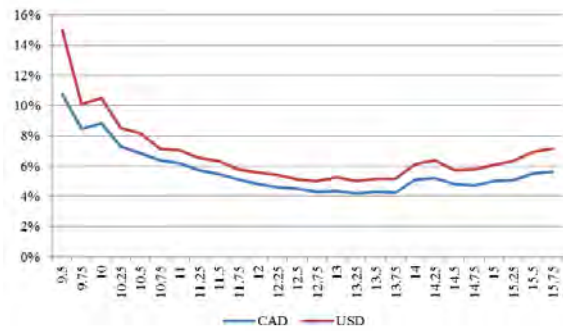
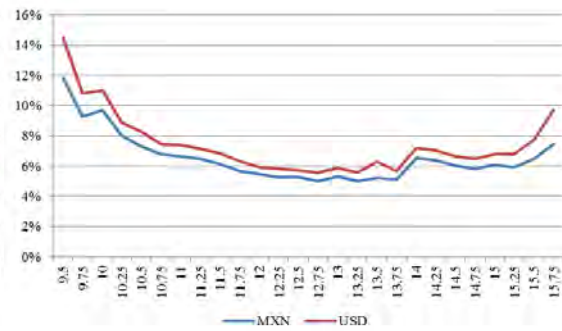


Figure 14: Synchronous ETP Range-based Volatility - USD versus Underlying Currency - Sep 2009 to Jul 2014

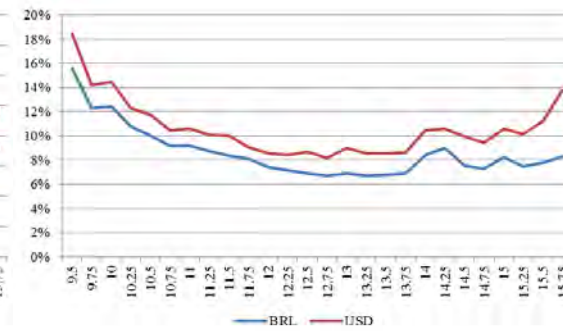
EWC – Canada



EWV – Mexico



EWZ – Brazil



8.3.1 Assessment of the Volatility Difference

Through visual inspection of Figure 12, Figure 13 and Figure 14 a difference between the range-based volatility, as measured in USD versus the range-based volatility as measured in the currency of the underlying securities basket, is observed. In all cases, the range-based volatility measured in the currency of the underlying securities is lower than that measured in USD. This indicates that the process of translating the NAV of the underlying basket into USD for the purpose of a USD NAV computation and USD denominated intraday pricing, introduces additional volatility. Grammig, Melvin and Schlag (2005) found that the foreign instruments in their study bore almost all the price adjustment to an exchange rate shock with the NYSE-listed ADRs repricing rather than the domestic securities. The findings of Grammig, Melvin and Schlag (2005) together with the observations of this thesis indicate a degree of currency risk is present in ETPs with foreign underlying securities and this risk feeds through into increased price volatility.

For each ETP the difference in range-based volatility between the USD measure and the local currency measure for each 15-minute interval is computed and those averaged differences presented in the table below.

Table 7: Average Difference in Range-based Volatility by Time Zone

Average Difference	
Non-Synchronous ETP	
Group Average	1.14%
EWA – Australia	1.11%
EWH – Hong Kong	1.27%
EWJ – Japan	0.92%
EWM – Malaysia	0.70%
EWS – Singapore	1.23%
EWT – Taiwan	1.46%
EWY – South Korea	1.29%
Partially Synchronous ETP	
Group Average	0.97%
EWD – Sweden	1.09%

EWG – Germany	1.06%
EWI – Italy	0.64%
EWK – Belgium	1.63%
EWL – Switzerland	0.96%
EWN – Netherlands	0.66%
EWO – Austria	1.14%
EWP – Spain	0.62%
EWQ – France	0.50%
EWU – United Kingdom	1.37%
Synchronous ETP	
Group Average	1.35%
EWC – Canada	1.15%
EWV – Mexico	0.90%
EWZ – Brazil	2.00%

We observe that that synchronous ETP group presents the highest average difference at a group level. However, the synchronous group contains the ETP which tracks a basket of underlying securities listed on the Brazilian stock exchange. This ETP with ticker EWZ shows the greatest average difference reflecting that the act of translating the price of the underlying securities from Brazilian Lira into USD introduces volatility to the USD price of the ETP. Surprisingly, the ETP tracking a basket of underlying securities listed on the Belgium stock exchange exhibits the second highest average difference in range-based volatility when measured in USD rather than Euros. Further investigation into the pricing transmission of the underlying securities prices would be required in order to explain this finding.

What is noticeable is, that on average, the volatility of the non-synchronous group measured in USD is higher than the volatility of the partially synchronous group measured in USD.

8.3.1.1 Assessment by Country Classification

The table below presents the same data as shown in Table 7, but rather than categorising the data by time zone of the underlying basket, we now cate-

gorise by the MSCI Country Classification Standard into emerging and developed market groups.

Table 8: Average Difference in Range-based Volatility by Country Classification

Average Difference	
Emerging Market	
Group Average	1.27%
EWM – Malaysia	0.70%
EWT – Taiwan	1.46%
EWV – Mexico	0.90%
EWY – South Korea	1.29%
EWZ – Brazil	2.00%
Developed Market	
Group Average	0.86%
EWA – Australia	0.00%
EWB – Canada	1.15%
EWJ – Sweden	1.09%
EWG – Germany	1.06%
EWH – Hong Kong	0.00%
EWI – Italy	0.64%
EWJ – Japan	0.92%
EWK – Belgium	1.63%
EWL – Switzerland	0.96%
EWN – Netherlands	0.66%
EWO – Austria	1.14%
EWP – Spain	0.62%
EWQ – France	0.50%
EWS – Singapore	1.23%
EWU – United Kingdom	1.37%

The emerging market group displays, on average, a higher level of volatility than the developed market group. Remembering that these measures indicate the level of increased range-based volatility when the underlying basket prices are translated into USD for the purposes of a USD denominated ETP instrument, these findings make intuitive sense. We would expect that the for-

eign exchange pairs of emerging market currencies against the USD would exhibit higher levels of volatility than those currency pairs of developed markets.

By contrasting the results obtained when the data were presented by time zone classification against the results obtained when the data were presented by country classification, we can again draw conclusions regarding the empirical outcomes of the analysis. When choosing to transact in an ETP whose underlying basket is denominated in an emerging market currency, additional care needs to be applied to an understanding and observation of the currency markets as well as the price fluctuations of the USD denominated ETP instrument.

As discussed in Section 6.3.1, the ETPs under review exhibit a U-shaped volatility profile with increased volatility at the start and end of the trading day. To understand the role currency translations play in during these beginning and ending periods, we display the average volatility difference during the period from 9.30am to 10:00am and from 3.30pm to 4:00pm versus the average volatility difference during the period from 10:00am to 3:30pm. The results are presented in the table below and are grouped by country classification.

Table 9: Average Difference in Range-based Volatility in First and Last 30 Minutes versus Remainder of Trading Day by Country Classification

	Average Difference	
	First and Last 30 Minutes	Excluding First and Last 30 Minutes
Emerging Market		
Group Average	2.24%	1.06%
EWM – Malaysia	1.88%	0.49%
EWT – Taiwan	1.46%	1.29%
EWV – Mexico	1.92%	0.71%
EWY – South Korea	2.51%	1.07%
EWZ – Brazil	3.44%	1.74%
Developed Market		
Group Average	1.78%	0.89%

EWA – Australia	1.94%	0.96%
EWB – Canada	2.19%	0.96%
EWJ – Sweden	2.41%	0.85%
EWG – Germany	2.75%	0.75%
EWK – Hong Kong	2.15%	1.10%
EWI – Italy	0.87%	0.60%
EWJ – Japan	1.38%	0.84%
EWK – Belgium	2.85%	1.40%
EWL – Switzerland	1.37%	0.89%
EWN – Netherlands	0.81%	0.63%
EWO – Austria	1.94%	0.99%
EWP – Spain	0.73%	0.60%
EWQ – France	0.59%	0.49%
EWS – Singapore	1.93%	1.10%
EWU – United Kingdom	2.74%	1.11%

Reviewing the data in Table 9 provides additional insight into the mechanisms at work. It is clear that decomposing the trading day periods into the first and last 30 minutes in the trading day versus the remainder of the trading day indicates that the impact of currency translation on range-based volatility is particularly noticeable at the beginning and end of the trading session. This effect is not only prevalent in emerging market currencies, but also in developed market currencies, with the increase in initial and final range-based volatility meaningful for ETPs with underlying baskets listed in Canada, Sweden, Germany, Hong Kong, Belgium, and the United Kingdom.

It suggests that the trading of ETPs with foreign underlying baskets at the start or end of the trading day is best avoided unless deeper awareness of the foreign exchange market environment is also incorporated into the trading decision making process.

Chapter 9

9 Conclusion

The research objective of this thesis was to conduct an empirical analysis of the effects on ETP price volatility that result when the ETP instrument is listed on an exchange that is in a different time zone to that of the underlying securities basket.

Recalling the study of Chan, Fong, Kho and Stulz (1996) who found that Japanese and European equities were most volatile during the US morning trading session and that of Chelley-Steeley and Park (2011) who found periods following a market closure were 20% more volatile than during regular periods, this thesis concludes that the US morning session does indeed present a higher volatility trading environment for not just equity securities but also for ETPs. The findings of this thesis confirm and support the findings of the prior, related literature. ETPs do exhibit increased volatility at the start of the US trading session and show a U-shaped volatility profile.

In the examination of the Flash Crash in Section 6.3.2.1 which provided an extreme view of the impact on ETP prices during a brief crisis period, Madhavan (2012) found that due to the distortion in equity prices that made up the underlying ETP baskets, there was an interruption in the natural arbitrage mechanisms which work to maintain ETP prices close to NAV. This interruption pushed ETP prices far from NAV and was a particularly volatile period. The interruption in the natural arbitrage mechanism is always present for the non-synchronous ETP group and for part of the US trading day for partially-synchronous ETPs.

In addition to the U-shaped volatility profile, the ETPs from the partially synchronous group undergo a “regime shift” during the transition period of an open to a closed underlying market during the US trading morning. This find-

ing is supportive of the study conducted by Levy and Lieberman (2013) who also found a change in the primary price driver for European ETPs as the underlying European markets closed.

From a practitioner's perspective, increased volatility in prices for the partially synchronous group suggests far greater care needs to be applied when transacting in these instruments. It is determined that the range-based volatility measured in the currency of the underlying securities is lower than that measured in USD. This indicates that the process of translating the NAV of the underlying basket into USD for the purpose of a USD NAV computation and USD denominated intraday pricing, introduces additional volatility.

Additionally, decomposing the trading day periods into the first and last 30 minutes in the trading day versus the remainder of the trading day indicates that the impact of currency translation on range-based volatility is particularly noticeable at the beginning and end of the trading session. This effect is not only prevalent in emerging market currencies, but also in developed market currencies.

These findings taken together emphasise the importance of the timing of trade execution when transacting in ETPs with foreign underlying security baskets. ETPs are undoubtedly useful instruments for institutional and retail investors, materially reducing the transactional cost and complexity of gaining investment exposure to foreign markets. For investors with medium to long term investment time horizons, increased volatility at the start or end of the trading day, or indeed for European ETPs during the European market close, is unlikely to create a material investment performance effect over the time horizon. However, for short-term market participants, the increased volatility during these periods could materially affect investment performance.

Irrespective of investment time horizon, it is prudent for those investors transacting in foreign ETPs to do so during periods in the market when volatility is typically low and price certainty is high.

Bibliography

Admati, A. R. & Pfleiderer, P., 1998. A theory of intraday patterns: volume and price variability. *The Review of Financial Studies*, 1(1), pp. 3-40.

Agarwal, S., Liu, C. & Rhee, S. G., 2007. Where does price discovery occur for stocks traded in multiple markets? Evidence from Hong Kong and London. *Journal of International Money and Finance*, Volume 26, pp. 46-63.

Alizadeh, S., Brandt, M. W. & Diebold, F. X., 2002. Range-based estimation of stochastic volatility models. *Journal of Finance*, p. 1047–1092.

Anderson, T. G., Bollerslev, T., Diebold, F. X. & Labys, P., 2001. The Distribution of Realized Exchange Rate Volatility. *Journal of the American Statistical Association*, Volume 96, pp. 42-55.

Baltagi, B., 2011. *Econometrics*. 5 ed. New York: Springer Science & Business Media.

Bennett, C. & Gil, M. A., 2012. *Measuring Historical Volatility*, Madrid: Santander Global Banking and Markets.

BlackRock Inc, 2013. *Exchange Traded Products: Overview, Benefits and Myths*, s.l.: s.n.

Brandt, M. W. & Diebold, F. X., 2006. A no-arbitrage approach to range-based estimation of return covariances and correlations. *Journal of Business*, Volume 79, p. 61–74.

Chan, K. C., Fong, W.-M., Kho, B.-C. & Stulz, R. M., 1996. Information, trading and stock returns: Lessons from dually-listed securities. *Journal of Banking & Finance*, Volume 20, pp. 1161-1187.

Chelley-Steeley, P. & Park, K., 2011. Intraday patterns in London listed Exchange Traded Funds. *International Review of Financial Analysis*, Volume 20, p. 244–251.

Chou, R. Y., Chou, H.-c. & Liu, N., 2009. Range Volatility Models and Their Applications in Finance. In: *The Handbook of Quantitative Finance and Risk Management*. s.l.:Springer.

Easley, D., Lopez de Prado, M. M. & O'Hara, M., 2011. The Microstructure of the "Flash Crash": Flow Toxicity, Liquidity Crashes, and the

Probability of Informed Trading. *The Journal of Portfolio Management*, 37(2), pp. 118-128.

Engle, R. & Sarkar, D., 2002. *Pricing Exchange Traded Funds*, s.l.: s.n.

Engle, R. & Sarkar, D., 2006. Premiums-Discounts and Exchange Traded Funds. *The Journal of Derivatives*, p. 27.

Eun, C. S. & Sabherwal, S., 2003. Cross-Border Listings and Price Discovery: Evidence from U.S.-Listed Canadian Stocks. *The Journal of Finance*, 58(2), pp. 549-575.

Eviews 8 Users Guide I, 2014. *Users Guide I*, s.l.: IHS Global Inc.

Feller, W., 1951. The asymptotic distribution of the range of sums of independent random variables. *The Annals of Mathematical Statistics*, September, 22(3), pp. 427-432.

Foster, D. & Viswanathan, 1993. Variation in trading volatility, and trading costs: Evidence on recent price formation models. *The Journal of Finance*, Volume 48, pp. 187-211.

Fuhr, D., 2014. *ETFGI LLP*. [Online] Available at: <http://www.etfgi.com/publications/reports/reportid/453> [Accessed 15 July 2014].

Fuller, W. A. & Dickey, D. A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, 74(366), pp. 427-431.

Garman, M. B. & Klaas, M. J., 1980. On the estimation of security price volatilities from historical data. *Journal of Business*, Volume 53, pp. 67-78.

Gastineau, G. L., 2001. An Introduction to Exchange-Traded Funds (ETFs). *Journal of Portfolio Management*.

Grammig, J., Melvin, M. & Schlag, C., 2005. Internationally cross-listed stock prices during overlapping trading hours: price discovery and exchange rate effects. *Journal of Empirical Finance*, Volume 12, pp. 139-164.

Guedj, I. & Huang, J., 2008. *Are ETFs Replacing Index Mutual Funds?*, s.l.: s.n.

Hamm, S. J. W., 2010. *The Effect of ETFs on Stock Liquidity*, Pennsylvania: University of Pennsylvania.

Hughen, J. C. & Mathew, P. G., 2009. The efficiency of international information flow: Evidence from the ETF and CEF prices. *International Review of Financial Analysis*, Volume 18, pp. 40-49.

Investment Company Institute, 2014. *2014 Investment Company Fact Book*, s.l.: Investment Company Institute.

Kwiatkowski, D., Phillips, P. C., Schmidt, P. & Shin, Y., 1992. How sure are we that economic time series have a unit root?. *Journal of Econometrics*, Volume 54, pp. 159-178.

Laerd Statistics, n.d. *Mann-Whitney U test in SPSS*. [Online] Available at: <https://statistics.laerd.com/premium-sample/mwut/mann-whitney-test-in-spss-2.php> [Accessed 26 April 2015].

Laerd Statistics, n.d. *Sign Test using SPSS*. [Online] Available at: <https://statistics.laerd.com/spss-tutorials/sign-test-using-spss-statistics.php> [Accessed 9 May 2015].

Levy, A. & Lieberman, O., 2013. Overreaction of country ETFs to US market returns: Intraday vs. daily horizons and the role of synchronized trading. *Journal of Banking & Finance*, Volume 37, p. 1412–1421.

Madhavan, A., 2012. Exchange-Traded Funds, Market Structure, and the Flash Crash. *Financial Analysts Journal*, 68(4), pp. 20-35.

Martens, M. & van Dijk, D., 2007. Measuring volatility with the realized range. *Journal of Econometrics*, 138(1), pp. 181-207.

Moulton, P. C. & Wei, L., 2005. *A Tale of Two Time Zones: Cross-Listed Stock Liquidity and the Availability of Substitutes*, New York: New York Stock Exchange.

MSCI Inc, 2014. *MSCI Country Classification Standard*. [Online] Available at: https://www.msci.com/resources/products/indexes/global_equity_indexes/gimi/stdindex/MSCI_Country_Classification_Standard.pdf [Accessed 23 May 2015].

MSCI Index Research, 2014. *MSCI Global Investable Market Indexes Methodology*, s.l.: s.n.

MSCI Index Research, 2014. *MSCI Global Investable Market Indexes Methodology Summary*, s.l.: s.n.

Ng, S. & Perron, P., 1995. Unit Root Tests in ARMA Models with Data-Dependent Methods for the Selection of the Truncation Lag. *Journal of the American Statistical Association*, 90(429), pp. 268-281.

Parkinson, M., 1980. The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business*, January, 53(1), pp. 61-65.

Petajisto, A., 2013. *Inefficiencies in the Pricing of Exchange Traded Funds*, s.l.: s.n.

Phillips, P. C. & Perron, P., 1988. Testing for a unit root in time series regression. *Biometrika*, 75(2), pp. 335-346.

Razali, N. M. & Wah, Y. B., 2011. Power comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests. *Journal of Statistical Modeling and Analytics*, 2(1), pp. 21-33.

Rompotis, G. G., 2010. Does premium impact Exchange-Traded Funds' returns? Evidence from iShares. *Journal of Asset Management*, 11(4), pp. 298-308.

Rosella, M. R. & Pugliese, D., 2006. The evolution of the exchange traded fund: is active management on the horizon?. *Journal of Investment Compliance*, 7(3), pp. 44-50.

Satchell, S. & Rogers, L., 1991. Estimating variance from High, Low and Closing Prices. *The Annals of Applied Probability*, 1(4), pp. 504-512.

Schwert, G. W., 1989. Tests for Unit Roots: A Monte Carlo Investigation. *Journal of Business & Economic Statistics*, 7(2), pp. 147-159.

Shamah, S., 2011. *A Foreign Exchange Primer*. 2, unabridged ed. s.l.:John Wiley & Sons.

Shu, J. & Zhang, J. E., 2006. Testing Range Estimators of Historical Volatility. *The Journal of Futures Markets*, 26(3), pp. 297-313.

Staffs of the CFTC and SEC, 2010. *Findings Regarding the Market Events of May 6, 2010*, New York: U.S. Commodity Futures Trading Commission & U.S. Securities & Exchange Commission.

Tannous, G., Wang, J. & Wilson, C., 2013. The Intraday Pattern of Information Asymmetry, Spread, and Depth: Evidence from the NYSE. *International Review of Finance*, 13(2), p. 215–240.

Thadewald, . T. & Büning, H., 2004. *Jarque-Bera test and its competitors for testing normality: A power comparison*, Berlin: Free University Berlin, School of Business & Economics.

Tse, Y. & Martinez, V., 2007. Price discovery and informational efficiency of international iShares funds. *Global Finance Journal*, Volume 18, pp. 1-15.

University of Paris-Sorbonne Economics Centre, na. *Choosing the Lag Length for the ADF Test*. [Online] Available at: <http://eurequa.univ-paris1.fr/membres/Ahamada/cours/nsss.pdf> [Accessed 19 May 2015].

Voraprateep, J., 2013. *Robustness of Wilcoxon Signed-Rank Test Against the Assumption of Symmetry*, Birmingham: School of Mathematics, University of Birmingham.

Yang, D. & Zhang, Q., 2000. Drift-Independent Volatility Estimation Based on High, Low, Open and Close Prices. *Journal of Business*, 73(3), pp. 477-491.

Yunus, N., 2013. Contagion in international financial markets: A recursive cointegration approach. *Journal of Multinational Financial Management*, 23(4), pp. 327-337.

Zivot, E., 2006. *Economics 584: Time Series Econometrics*. [Online] Available at: <http://faculty.washington.edu/ezivot/econ584/econ584.htm>

Appendices

Appendix A

A.1 Shapiro-Wilk Test Statistics

Appendix Table 1: Shapiro-Wilk Test Results for Non-Synchronous ETPs - Jan 2006 to Jul 2014 - Non-Aggregated Data

Time	EWA Australia		EWH Hong Kong		EWJ Japan		EWM Malaysia		EWS Singapore		EWT Taiwan		EWY South Korea	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	0.164	0.000	0.208	0.000	0.149	0.000	0.132	0.000	0.098	0.000	0.204	0.000	0.161	0.000
09:45	0.175	0.000	0.249	0.000	0.317	0.000	0.016	0.000	0.015	0.000	0.267	0.000	0.134	0.000
10:00	0.330	0.000	0.317	0.000	0.349	0.000	0.131	0.000	0.197	0.000	0.206	0.000	0.390	0.000
10:15	0.350	0.000	0.300	0.000	0.453	0.000	0.038	0.000	0.432	0.000	0.405	0.000	0.291	0.000
10:30	0.338	0.000	0.336	0.000	0.354	0.000	0.189	0.000	0.384	0.000	0.232	0.000	0.273	0.000
10:45	0.319	0.000	0.286	0.000	0.262	0.000	0.133	0.000	0.323	0.000	0.064	0.000	0.275	0.000
11:00	0.236	0.000	0.273	0.000	0.165	0.000	0.152	0.000	0.263	0.000	0.264	0.000	0.320	0.000
11:15	0.308	0.000	0.331	0.000	0.385	0.000	0.041	0.000	0.351	0.000	0.323	0.000	0.176	0.000
11:30	0.279	0.000	0.021	0.000	0.559	0.000	0.332	0.000	0.435	0.000	0.403	0.000	0.154	0.000
11:45	0.300	0.000	0.341	0.000	0.432	0.000	0.372	0.000	0.279	0.000	0.027	0.000	0.283	0.000
12:00	0.250	0.000	0.355	0.000	0.351	0.000	0.282	0.000	0.237	0.000	0.276	0.000	0.267	0.000
12:15	0.339	0.000	0.321	0.000	0.396	0.000	0.365	0.000	0.354	0.000	0.348	0.000	0.278	0.000
12:30	0.349	0.000	0.276	0.000	0.349	0.000	0.281	0.000	0.249	0.000	0.242	0.000	0.281	0.000
12:45	0.211	0.000	0.337	0.000	0.421	0.000	0.168	0.000	0.321	0.000	0.291	0.000	0.274	0.000
13:00	0.352	0.000	0.385	0.000	0.174	0.000	0.281	0.000	0.128	0.000	0.169	0.000	0.214	0.000

Time	EWA Australia		EWH Hong Kong		EWJ Japan		EWM Malaysia		EWS Singapore		EWT Taiwan		EWY South Korea	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
13:15	0.259	0.000	0.319	0.000	0.327	0.000	0.307	0.000	0.323	0.000	0.299	0.000	0.213	0.000
13:30	0.289	0.000	0.311	0.000	0.355	0.000	0.184	0.000	0.218	0.000	0.319	0.000	0.328	0.000
13:45	0.239	0.000	0.138	0.000	0.251	0.000	0.134	0.000	0.125	0.000	0.223	0.000	0.055	0.000
14:00	0.236	0.000	0.226	0.000	0.309	0.000	0.199	0.000	0.225	0.000	0.169	0.000	0.178	0.000
14:15	0.165	0.000	0.254	0.000	0.273	0.000	0.294	0.000	0.301	0.000	0.231	0.000	0.233	0.000
14:30	0.231	0.000	0.314	0.000	0.384	0.000	0.324	0.000	0.281	0.000	0.300	0.000	0.304	0.000
14:45	0.035	0.000	0.312	0.000	0.399	0.000	0.351	0.000	0.325	0.000	0.326	0.000	0.318	0.000
15:00	0.240	0.000	0.292	0.000	0.253	0.000	0.299	0.000	0.089	0.000	0.190	0.000	0.236	0.000
15:15	0.144	0.000	0.158	0.000	0.298	0.000	0.274	0.000	0.299	0.000	0.294	0.000	0.217	0.000
15:30	0.250	0.000	0.121	0.000	0.298	0.000	0.089	0.000	0.233	0.000	0.169	0.000	0.260	0.000
15:45	0.209	0.000	0.188	0.000	0.242	0.000	0.276	0.000	0.222	0.000	0.171	0.000	0.149	0.000

Appendix Table 2: Shapiro-Wilk Test Results for Partially Synchronous ETPs - Jan 2006 to Jul 2014 - Non-Aggregated Data

Time	EWD Sweden		EWG Germany		EWI Italy		EWK Belgium		EWL Switzerland		EWN Netherlands		EWO Austria		EWP Spain		EWQ France		EWU United Kingdom	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	0.060	0.000	0.062	0.000	0.280	0.000	0.352	0.000	0.369	0.000	0.258	0.000	0.250	0.000	0.096	0.000	0.262	0.000	0.051	0.000
09:45	0.362	0.000	0.125	0.000	0.142	0.000	0.026	0.000	0.400	0.000	0.047	0.000	0.021	0.000	0.038	0.000	0.266	0.000	0.000	0.000
10:00	0.300	0.000	0.108	0.000	0.116	0.000	0.038	0.000	0.340	0.000	0.197	0.000	0.017	0.000	0.202	0.000	0.343	0.000	0.021	0.000
10:15	0.438	0.000	0.331	0.000	0.281	0.000	0.180	0.000	0.381	0.000	0.280	0.000	0.035	0.000	0.341	0.000	0.369	0.000	0.318	0.000
10:30	0.429	0.000	0.378	0.000	0.434	0.000	0.276	0.000	0.415	0.000	0.303	0.000	0.180	0.000	0.362	0.000	0.322	0.000	0.308	0.000
10:45	0.343	0.000	0.352	0.000	0.510	0.000	0.149	0.000	0.378	0.000	0.245	0.000	0.100	0.000	0.469	0.000	0.457	0.000	0.366	0.000
11:00	0.330	0.000	0.298	0.000	0.385	0.000	0.106	0.000	0.211	0.000	0.095	0.000	0.226	0.000	0.300	0.000	0.275	0.000	0.388	0.000
11:15	0.267	0.000	0.339	0.000	0.289	0.000	0.118	0.000	0.087	0.000	0.039	0.000	0.166	0.000	0.300	0.000	0.294	0.000	0.370	0.000
11:30	0.192	0.000	0.298	0.000	0.386	0.000	0.035	0.000	0.338	0.000	0.108	0.000	0.319	0.000	0.435	0.000	0.416	0.000	0.394	0.000
11:45	0.351	0.000	0.270	0.000	0.400	0.000	0.213	0.000	0.408	0.000	0.359	0.000	0.120	0.000	0.422	0.000	0.374	0.000	0.095	0.000
12:00	0.269	0.000	0.116	0.000	0.437	0.000	0.149	0.000	0.335	0.000	0.204	0.000	0.117	0.000	0.341	0.000	0.263	0.000	0.333	0.000
12:15	0.250	0.000	0.251	0.000	0.355	0.000	0.136	0.000	0.249	0.000	0.255	0.000	0.193	0.000	0.281	0.000	0.271	0.000	0.301	0.000

Time	EWD Sweden		EWG Germany		EWI Italy		EWK Belgium		EWL Switzerland		EWN Netherlands		EWO Austria		EWP Spain		EWQ France		EWU United Kingdom	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
12:30	0.287	0.000	0.111	0.000	0.325	0.000	0.197	0.000	0.308	0.000	0.201	0.000	0.125	0.000	0.185	0.000	0.250	0.000	0.309	0.000
12:45	0.221	0.000	0.261	0.000	0.231	0.000	0.220	0.000	0.214	0.000	0.214	0.000	0.012	0.000	0.338	0.000	0.248	0.000	0.250	0.000
13:00	0.286	0.000	0.309	0.000	0.143	0.000	0.244	0.000	0.343	0.000	0.304	0.000	0.092	0.000	0.377	0.000	0.350	0.000	0.022	0.000
13:15	0.265	0.000	0.305	0.000	0.264	0.000	0.119	0.000	0.091	0.000	0.294	0.000	0.103	0.000	0.014	0.000	0.302	0.000	0.239	0.000
13:30	0.257	0.000	0.315	0.000	0.392	0.000	0.144	0.000	0.324	0.000	0.251	0.000	0.090	0.000	0.285	0.000	0.331	0.000	0.113	0.000
13:45	0.231	0.000	0.149	0.000	0.343	0.000	0.240	0.000	0.155	0.000	0.169	0.000	0.088	0.000	0.161	0.000	0.186	0.000	0.126	0.000
14:00	0.251	0.000	0.254	0.000	0.256	0.000	0.014	0.000	0.286	0.000	0.013	0.000	0.100	0.000	0.359	0.000	0.143	0.000	0.259	0.000
14:15	0.181	0.000	0.175	0.000	0.228	0.000	0.168	0.000	0.293	0.000	0.171	0.000	0.151	0.000	0.208	0.000	0.151	0.000	0.229	0.000
14:30	0.326	0.000	0.265	0.000	0.312	0.000	0.220	0.000	0.242	0.000	0.156	0.000	0.265	0.000	0.299	0.000	0.186	0.000	0.257	0.000
14:45	0.172	0.000	0.228	0.000	0.334	0.000	0.259	0.000	0.304	0.000	0.243	0.000	0.136	0.000	0.341	0.000	0.303	0.000	0.296	0.000
15:00	0.313	0.000	0.265	0.000	0.286	0.000	0.137	0.000	0.217	0.000	0.297	0.000	0.083	0.000	0.184	0.000	0.193	0.000	0.244	0.000
15:15	0.189	0.000	0.226	0.000	0.266	0.000	0.158	0.000	0.221	0.000	0.194	0.000	0.133	0.000	0.286	0.000	0.215	0.000	0.273	0.000
15:30	0.148	0.000	0.133	0.000	0.325	0.000	0.167	0.000	0.088	0.000	0.230	0.000	0.171	0.000	0.253	0.000	0.064	0.000	0.105	0.000
15:45	0.199	0.000	0.185	0.000	0.404	0.000	0.144	0.000	0.177	0.000	0.105	0.000	0.119	0.000	0.025	0.000	0.019	0.000	0.116	0.000

Appendix Table 3: Shapiro-Wilk Test Results for Synchronous ETPs - Jan 2006 to Jul 2014 - Non-Aggregated Data

Time	EWC Canada		EWW Mexico		EWZ Brazil		IVV United States	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	0.153	0.000	0.220	0.000	0.205	0.000	0.088	0.000
09:45	0.012	0.000	0.160	0.000	0.302	0.000	0.298	0.000
10:00	0.230	0.000	0.173	0.000	0.290	0.000	0.264	0.000
10:15	0.438	0.000	0.402	0.000	0.078	0.000	0.346	0.000
10:30	0.394	0.000	0.250	0.000	0.311	0.000	0.299	0.000
10:45	0.293	0.000	0.335	0.000	0.310	0.000	0.301	0.000
11:00	0.356	0.000	0.307	0.000	0.295	0.000	0.185	0.000
11:15	0.271	0.000	0.116	0.000	0.268	0.000	0.291	0.000

11:30	0.213	0.000	0.296	0.000	0.356	0.000	0.348	0.000
11:45	0.277	0.000	0.420	0.000	0.234	0.000	0.241	0.000
12:00	0.306	0.000	0.348	0.000	0.181	0.000	0.265	0.000
12:15	0.239	0.000	0.324	0.000	0.231	0.000	0.275	0.000
12:30	0.285	0.000	0.365	0.000	0.198	0.000	0.243	0.000
12:45	0.345	0.000	0.346	0.000	0.216	0.000	0.257	0.000
13:00	0.374	0.000	0.249	0.000	0.226	0.000	0.396	0.000
13:15	0.297	0.000	0.250	0.000	0.237	0.000	0.278	0.000
13:30	0.113	0.000	0.161	0.000	0.312	0.000	0.291	0.000
13:45	0.230	0.000	0.139	0.000	0.148	0.000	0.080	0.000
14:00	0.260	0.000	0.275	0.000	0.217	0.000	0.170	0.000
14:15	0.233	0.000	0.131	0.000	0.190	0.000	0.221	0.000
14:30	0.253	0.000	0.253	0.000	0.025	0.000	0.288	0.000
14:45	0.300	0.000	0.308	0.000	0.141	0.000	0.265	0.000
15:00	0.240	0.000	0.161	0.000	0.175	0.000	0.211	0.000
15:15	0.199	0.000	0.132	0.000	0.253	0.000	0.260	0.000
15:30	0.125	0.000	0.147	0.000	0.085	0.000	0.122	0.000
15:45	0.176	0.000	0.064	0.000	0.101	0.000	0.178	0.000

A.2 Jarque-Bera Test Statistics

Appendix Table 4: Jarque-Bera Test Results for Non-Synchronous ETPs - Jan 2006 to Jul 2014 - Non-Aggregated Data

Time	EWA Australia		EWH Hong Kong		EWJ Japan		EWM Malaysia		EWS Singapore		EWT Taiwan		EWY South Korea	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	2 202 811	0.000	3 286 839	0.000	10 727 735	0.000	3 306 686	0.000	11 827 378	0.000	6 176 770	0.000	6 575 619	0.000
09:45	38 036 622	0.000	13 047 734	0.000	6 651 724	0.000	389 000 000	0.000	400 000 000	0.000	7 353 405	0.000	80 721 290	0.000
10:00	8 144 329	0.000	5 636 887	0.000	3 186 672	0.000	57 850 890	0.000	11 758 621	0.000	92 056 781	0.000	495 417	0.000

Time	EWA Australia		EWH Hong Kong		EWJ Japan		EWM Malaysia		EWS Singapore		EWT Taiwan		EWY South Korea	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
10:15	1 417 314	0.000	1 870 174	0.000	647 649	0.000	243 000 000	0.000	271 818	0.000	376 934	0.000	7 815 086	0.000
10:30	1 789 207	0.000	2 910 807	0.000	1 166 543	0.000	45 472 157	0.000	436 352	0.000	31 170 406	0.000	1 951 411	0.000
10:45	1 149 194	0.000	8 923 559	0.000	9 093 189	0.000	73 650 096	0.000	2 153 547	0.000	254 000 000	0.000	2 876 612	0.000
11:00	8 417 762	0.000	15 165 975	0.000	95 005 291	0.000	54 545 113	0.000	9 716 901	0.000	3 489 588	0.000	1 037 331	0.000
11:15	863 779	0.000	1 232 577	0.000	532 699	0.000	324 000 000	0.000	975 566	0.000	1 523 530	0.000	59 729 144	0.000
11:30	7 680 758	0.000	387 000 000	0.000	71 036	0.000	1 347 527	0.000	500 197	0.000	474 379	0.000	64 135 431	0.000
11:45	6 486 551	0.000	3 853 406	0.000	375 288	0.000	1 422 954	0.000	8 382 666	0.000	366 000 000	0.000	2 956 062	0.000
12:00	9 494 320	0.000	1 551 654	0.000	4 472 865	0.000	4 822 050	0.000	15 760 749	0.000	6 780 722	0.000	4 094 272	0.000
12:15	1 223 574	0.000	1 253 832	0.000	879 400	0.000	755 604	0.000	749 053	0.000	603 179	0.000	1 313 232	0.000
12:30	517 560	0.000	3 085 555	0.000	902 609	0.000	7 585 990	0.000	10 987 781	0.000	14 262 048	0.000	3 581 248	0.000
12:45	8 433 300	0.000	987 395	0.000	307 278	0.000	63 187 492	0.000	1 193 907	0.000	1 727 077	0.000	1 867 348	0.000
13:00	2 412 294	0.000	489 893	0.000	114 000 000	0.000	5 077 222	0.000	149 000 000	0.000	54 753 983	0.000	26 148 574	0.000
13:15	11 767 036	0.000	1 436 390	0.000	3 344 622	0.000	2 367 978	0.000	1 595 788	0.000	1 497 635	0.000	6 255 117	0.000
13:30	3 561 924	0.000	1 983 066	0.000	1 363 728	0.000	30 669 366	0.000	18 887 588	0.000	1 156 433	0.000	621 809	0.000
13:45	4 798 631	0.000	62 267 548	0.000	15 155 503	0.000	58 794 360	0.000	110 000 000	0.000	10 538 679	0.000	281 000 000	0.000
14:00	8 391 449	0.000	10 994 046	0.000	3 373 510	0.000	10 917 342	0.000	11 366 437	0.000	37 446 719	0.000	12 372 722	0.000
14:15	23 194 409	0.000	1 930 373	0.000	3 720 495	0.000	807 963	0.000	1 094 015	0.000	5 174 471	0.000	2 397 526	0.000
14:30	2 315 656	0.000	796 410	0.000	345 448	0.000	642 877	0.000	1 810 225	0.000	959 306	0.000	828 861	0.000
14:45	328 000 000	0.000	790 080	0.000	647 327	0.000	367 722	0.000	1 420 207	0.000	407 043	0.000	1 025 498	0.000
15:00	1 603 360	0.000	764 508	0.000	7 239 153	0.000	1 094 936	0.000	185 000 000	0.000	8 833 742	0.000	2 820 076	0.000
15:15	36 778 745	0.000	64 809 758	0.000	1 788 345	0.000	1 990 074	0.000	1 368 220	0.000	1 088 474	0.000	15 868 183	0.000
15:30	2 286 220	0.000	43 984 406	0.000	2 901 717	0.000	165 000 000	0.000	4 186 171	0.000	34 570 909	0.000	1 057 541	0.000
15:45	3 202 676	0.000	29 328 354	0.000	2 746 099	0.000	1 423 821	0.000	9 608 140	0.000	6 272 382	0.000	28 477 634	0.000

Appendix Table 5: Jarque-Bera Test Results for Partially Synchronous ETPs - Jan 2006 to Jul 2014 - Non-Aggregated Data

Time	EWD Sweden		EWG Germany		EWI Italy		EWK Belgium		EWL Switzerland	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	820 392	0.000	3 816 252	0.000	684 702	0.000	1 413	0.000	169 834	0.000
09:45	2 233 115	0.000	64 648 494	0.000	59 848 727	0.000	128 000 000	0.000	1 170 810	0.000
10:00	2 191 123	0.000	184 000 000	0.000	144 000 000	0.000	99 630 755	0.000	2 082 570	0.000
10:15	297 996	0.000	1 678 955	0.000	7 065 420	0.000	11 580 037	0.000	785 038	0.000
10:30	360 550	0.000	2 038 226	0.000	287 963	0.000	881 732	0.000	893 678	0.000
10:45	1 615 849	0.000	2 016 945	0.000	107 792	0.000	14 220 328	0.000	332 044	0.000
11:00	2 423 748	0.000	1 772 389	0.000	740 911	0.000	19 205 595	0.000	21 786 148	0.000
11:15	13 130 599	0.000	598 616	0.000	12 792 835	0.000	21 751 229	0.000	192 000 000	0.000
11:30	36 189 990	0.000	2 877 604	0.000	574 179	0.000	100 000 000	0.000	908 006	0.000
11:45	930 745	0.000	7 856 965	0.000	421 409	0.000	6 979 912	0.000	643 690	0.000
12:00	8 761 179	0.000	158 000 000	0.000	239 831	0.000	19 175 693	0.000	1 545 909	0.000
12:15	2 851 952	0.000	2 042 949	0.000	534 534	0.000	16 247 856	0.000	9 364 082	0.000
12:30	1 465 048	0.000	95 217 283	0.000	1 207 060	0.000	3 449 118	0.000	1 355 550	0.000
12:45	5 728 669	0.000	3 175 605	0.000	11 607 404	0.000	5 276 968	0.000	7 355 242	0.000
13:00	1 779 118	0.000	5 977 808	0.000	61 923 054	0.000	1 522 883	0.000	1 585 974	0.000
13:15	7 612 346	0.000	1 863 281	0.000	1 618 162	0.000	14 885 832	0.000	111 000 000	0.000
13:30	2 772 852	0.000	2 237 471	0.000	239 186	0.000	24 592 200	0.000	521 418	0.000
13:45	9 525 546	0.000	64 807 036	0.000	760 345	0.000	784 671	0.000	49 421 800	0.000
14:00	6 209 207	0.000	3 165 648	0.000	12 902 479	0.000	85 228 688	0.000	1 085 196	0.000
14:15	10 006 751	0.000	13 307 012	0.000	3 595 308	0.000	3 018 079	0.000	992 298	0.000
14:30	427 262	0.000	2 192 317	0.000	511 131	0.000	3 250 742	0.000	1 749 763	0.000
14:45	15 859 879	0.000	5 565 394	0.000	1 433 009	0.000	1 899 432	0.000	865 499	0.000
15:00	839 293	0.000	2 105 227	0.000	1 332 157	0.000	10 215 189	0.000	4 557 920	0.000
15:15	13 085 413	0.000	4 548 679	0.000	2 715 573	0.000	5 698 294	0.000	15 112 485	0.000
15:30	34 146 866	0.000	32 508 620	0.000	1 851 080	0.000	4 853 071	0.000	151 000 000	0.000
15:45	13 560 342	0.000	9 238 213	0.000	613 711	0.000	16 978 301	0.000	33 323 928	0.000

Time	EWN Netherlands		EWO Austria		EWP Spain		EWQ France		EWU United Kingdom	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	56 958	0.000	15 664	0.000	1 595 130	0.000	382 409	0.000	11 513 163	0.000
09:45	75 752 849	0.000	223 000 000	0.000	189 000 000	0.000	4 689 522	0.000	NA	NA
10:00	16 875 983	0.000	206 000 000	0.000	16 192 813	0.000	6 395 407	0.000	385 000 000	0.000
10:15	1 937 133	0.000	49 935 342	0.000	2 511 555	0.000	710 080	0.000	2 434 521	0.000
10:30	7 394 073	0.000	29 618 487	0.000	2 416 901	0.000	1 401 808	0.000	5 772 136	0.000
10:45	4 939 760	0.000	30 124 169	0.000	353 339	0.000	204 151	0.000	925 462	0.000
11:00	101 000 000	0.000	3 908 485	0.000	2 474 959	0.000	4 604 680	0.000	478 518	0.000
11:15	143 000 000	0.000	24 049 990	0.000	10 360 107	0.000	2 887 301	0.000	721 080	0.000
11:30	60 100 383	0.000	984 898	0.000	280 223	0.000	417 861	0.000	1 067 093	0.000
11:45	460 355	0.000	36 232 583	0.000	431 946	0.000	873 704	0.000	201 000 000	0.000
12:00	1 892 512	0.000	20 365 334	0.000	531 493	0.000	1 859 381	0.000	1 635 434	0.000
12:15	956 302	0.000	1 841 832	0.000	2 204 049	0.000	7 469 653	0.000	3 815 263	0.000
12:30	4 978 703	0.000	40 267 184	0.000	24 265 504	0.000	2 210 620	0.000	1 692 966	0.000
12:45	5 106 368	0.000	145 000 000	0.000	946 251	0.000	9 379 270	0.000	2 413 183	0.000
13:00	424 893	0.000	11 724 039	0.000	324 513	0.000	482 995	0.000	353 000 000	0.000
13:15	777 115	0.000	9 416 626	0.000	290 000 000	0.000	995 269	0.000	2 749 936	0.000
13:30	1 002 642	0.000	21 634 912	0.000	3 382 682	0.000	689 797	0.000	105 000 000	0.000
13:45	5 747 903	0.000	51 653 083	0.000	29 651 588	0.000	12 864 528	0.000	33 551 296	0.000
14:00	148 000 000	0.000	12 932 655	0.000	912 295	0.000	31 006 580	0.000	4 440 781	0.000
14:15	4 677 242	0.000	16 280 053	0.000	4 585 292	0.000	8 354 998	0.000	2 311 694	0.000
14:30	4 731 774	0.000	2 469 216	0.000	696 105	0.000	23 920 374	0.000	2 799 463	0.000
14:45	1 311 098	0.000	9 564 516	0.000	513 076	0.000	1 291 624	0.000	1 983 610	0.000
15:00	1 406 567	0.000	88 185 464	0.000	17 237 657	0.000	5 368 265	0.000	3 423 579	0.000
15:15	3 235 198	0.000	11 281 048	0.000	2 726 354	0.000	6 834 811	0.000	2 532 291	0.000
15:30	1 207 786	0.000	3 804 934	0.000	3 373 269	0.000	128 000 000	0.000	49 509 858	0.000
15:45	26 103 674	0.000	26 345 006	0.000	339 000 000	0.000	342 000 000	0.000	94 125 204	0.000

Appendix Table 6: Jarque-Bera Test Results for Synchronous ETPs - Jan 2006 to Jul 2014 - Non-Aggregated Data

	EWC		EWW		EWZ		IVV	
	Canada		Mexico		Brazil		United States	
	Stat	p-value	Stat	p-value	Stat	p-value	Stat	p-value
09:30	2 740 355	0.000	2 646 993	0.000	2 376 556	0.000	76 211 438	0.000
09:45	401 000 000	0.000	46 187 720	0.000	2 106 877	0.000	2 044 213	0.000
10:00	34 061 556	0.000	76 496 189	0.000	8 811 558	0.000	16 670 291	0.000
10:15	316 871	0.000	995 941	0.000	119 000 000	0.000	998 469	0.000
10:30	1 578 536	0.000	13 550 429	0.000	609 524	0.000	4 878 438	0.000
10:45	7 331 711	0.000	1 535 539	0.000	646 039	0.000	1 534 465	0.000
11:00	753 550	0.000	1 333 893	0.000	939 478	0.000	15 848 761	0.000
11:15	4 027 729	0.000	137 000 000	0.000	1 401 980	0.000	1 012 070	0.000
11:30	72 963 548	0.000	3 455 703	0.000	322 688	0.000	728 519	0.000
11:45	4 693 002	0.000	769 146	0.000	2 521 640	0.000	18 302 497	0.000
12:00	2 715 551	0.000	3 245 765	0.000	8 030 243	0.000	11 874 743	0.000
12:15	2 816 820	0.000	1 867 954	0.000	5 000 127	0.000	3 891 857	0.000
12:30	1 785 631	0.000	769 418	0.000	3 812 307	0.000	5 453 998	0.000
12:45	1 289 522	0.000	509 701	0.000	11 227 518	0.000	2 714 163	0.000
13:00	836 524	0.000	19 125 772	0.000	3 569 040	0.000	201 767	0.000
13:15	2 012 497	0.000	6 192 556	0.000	2 356 345	0.000	2 397 452	0.000
13:30	109 000 000	0.000	73 490 299	0.000	429 202	0.000	915 097	0.000
13:45	8 417 292	0.000	64 568 581	0.000	21 887 249	0.000	173 000 000	0.000
14:00	9 293 441	0.000	2 653 162	0.000	2 681 732	0.000	23 259 477	0.000
14:15	1 921 785	0.000	103 000 000	0.000	7 134 466	0.000	4 331 092	0.000
14:30	2 213 761	0.000	12 323 468	0.000	82 467 787	0.000	868 402	0.000
14:45	890 919	0.000	2 729 418	0.000	58 223 593	0.000	1 823 836	0.000
15:00	3 075 539	0.000	10 455 770	0.000	4 111 640	0.000	4 591 690	0.000
15:15	15 733 713	0.000	76 934 731	0.000	1 265 031	0.000	2 820 379	0.000
15:30	106 000 000	0.000	68 781 139	0.000	23 025 727	0.000	90 580 300	0.000
15:45	7 788 931	0.000	103 000 000	0.000	12 646 404	0.000	17 495 478	0.000

Appendix B

B.1 ADF Test Statistics

Appendix Table 7: ADF Test Results for Non-Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

EWA			EWH			EWJ		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 23 (Fixed)			Lag Length: 19 (Fixed)			Lag Length: 21 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	7.610	1	Augmented Dickey-Fuller test statistic	18.924	1	Augmented Dickey-Fuller test statistic	15.909	1
Test critical values: 1% level	-2.566		Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		
EWM			EWS			EWT		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 23 (Fixed)			Lag Length: 24 (Fixed)			Lag Length: 24 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	22.324	1	Augmented Dickey-Fuller test statistic	7.944	1	Augmented Dickey-Fuller test statistic	8.863	1
Test critical values: 1% level	-2.566		Test critical values: 1% level	-2.567		Test critical values: 1% level	-2.567	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.616		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		

EWY

Null Hypothesis: ALL_DISC has a unit root
Exogenous: None
Lag Length: 24 (Fixed)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	0.881	0.8988
Test critical values: 1% level	-2.567	
5% level	-1.941	
10% level	-1.617	

*MacKinnon (1996) one-sided p-values.

Appendix Table 8: ADF Test Results for Partially Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

EWD			EWG			EWI		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 24 (Fixed)			Lag Length: 22 (Fixed)			Lag Length: 23 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	3.770	1	Augmented Dickey-Fuller test statistic	15.196	1	Augmented Dickey-Fuller test statistic	1.596	0.9734
Test critical values: 1% level	-2.576		Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.567	
5% level	-1.942		5% level	-1.941		5% level	-1.941	
10% level	-1.616		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		
EWK			EWL			EWN		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 22 (Fixed)			Lag Length: 24 (Fixed)			Lag Length: 23 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	3.440	0.9999	Augmented Dickey-Fuller test statistic	2.036	0.9903	Augmented Dickey-Fuller test statistic	-0.386	0.5448
Test critical values: 1% level	-2.568		Test critical values: 1% level	-2.574		Test critical values: 1% level	-2.570	

*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		
5% level	-1.941		5% level	-1.942		5% level	-1.942	
10% level	-1.616		10% level	-1.616		10% level	-1.616	
EWO			EWP			EWQ		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 24 (Fixed)			Lag Length: 23 (Fixed)			Lag Length: 23 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	2.039	0.9891	Augmented Dickey-Fuller test statistic	2.985	0.9994	Augmented Dickey-Fuller test statistic	2.656	0.9983
Test critical values: 1% level	-2.615		Test critical values: 1% level	-2.566		Test critical values: 1% level	-2.566	
5% level	-1.948		5% level	-1.941		5% level	-1.941	
10% level	-1.612		10% level	-1.617		10% level	-1.617	
EWO			EWP			EWQ		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 17 (Fixed)			Lag Length: 17 (Fixed)			Lag Length: 17 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	26.945	1	Augmented Dickey-Fuller test statistic	26.945	1	Augmented Dickey-Fuller test statistic	26.945	1
Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
EWO			EWP			EWQ		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 17 (Fixed)			Lag Length: 17 (Fixed)			Lag Length: 17 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	26.945	1	Augmented Dickey-Fuller test statistic	26.945	1	Augmented Dickey-Fuller test statistic	26.945	1
Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	

Appendix Table 9: ADF Test Results for Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

IVV			EWC			EWW		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Lag Length: 24 (Fixed)			Lag Length: 24 (Fixed)			Lag Length: 23 (Fixed)		
	t-Statistic	Prob.*		t-Statistic	Prob.*		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	4.251	1	Augmented Dickey-Fuller test statistic	1.080	0.9274	Augmented Dickey-Fuller test statistic	12.770	1
Test critical values: 1% level	-2.566		Test critical values: 1% level	-2.567		Test critical values: 1% level	-2.566	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.616		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		
EWZ								
Null Hypothesis: ALL_DISC has a unit root								
Exogenous: None								
Lag Length: 24 (Fixed)								
	t-Statistic	Prob.*						
Augmented Dickey-Fuller test statistic	9.811	1						
Test critical values: 1% level	-2.566							
5% level	-1.941							
10% level	-1.617							
*MacKinnon (1996) one-sided p-values.								

B.2 Phillips-Perron Test Statistics

Appendix Table 10: Phillips-Perron Test Results for Non-Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

EWA			EWH			EWJ		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Bandwidth: 155 (Newey-West automatic) using Bartlett kernel			Bandwidth: 150 (Newey-West automatic) using Bartlett kernel			Bandwidth: 157 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-363.586	0.0001	Phillips-Perron test statistic	-372.836	0.0001	Phillips-Perron test statistic	-363.059	0.0001
Test critical values:			Test critical values:			Test critical values:		
1% level	-2.565		1% level	-2.565		1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		
EWM			EWS			EWT		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Bandwidth: 91 (Newey-West automatic) using Bartlett kernel			Bandwidth: 101 (Newey-West automatic) using Bartlett kernel			Bandwidth: 152 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-223.036	0.0001	Phillips-Perron test statistic	-172.540	0.0001	Phillips-Perron test statistic	-402.549	0.0001
Test critical values:			Test critical values:			Test critical values:		
1% level	-2.565		1% level	-2.565		1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		

EWY

Null Hypothesis: ALL_DISC has a unit root

Exogenous: None

Bandwidth: 154 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-396.220	0.0001
Test critical values: 1% level	-2.565	
5% level	-1.941	
10% level	-1.617	

*MacKinnon (1996) one-sided p-values.

Appendix Table 11: Phillips-Perron Test Results for Partially Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

EWD			EWG			EWI		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Bandwidth: 147 (Newey-West automatic) using Bartlett kernel			Bandwidth: 159 (Newey-West automatic) using Bartlett kernel			Bandwidth: 133 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-335.479	0.0001	Phillips-Perron test statistic	-317.37	0.0001	Phillips-Perron test statistic	-325.065	0.0001
Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.57		Test critical values: 1% level	-2.565	
5% level	-1.941		5% level	-1.94		5% level	-1.941	
10% level	-1.617		10% level	-1.62		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		

EWK			EWL			EWN		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Bandwidth: 49 (Newey-West automatic) using Bartlett kernel			Bandwidth: 138 (Newey-West automatic) using Bartlett kernel			Bandwidth: 53 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-172.219	0.0001	Phillips-Perron test statistic	-312.316	0.0001	Phillips-Perron test statistic	-184.151	0.0001
Test critical values:			Test critical values:			Test critical values:		
1% level	-2.565		1% level	-2.565		1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		
EWO			EWP			EWQ		
Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root			Null Hypothesis: ALL_DISC has a unit root		
Exogenous: None			Exogenous: None			Exogenous: None		
Bandwidth: 65 (Newey-West automatic) using Bartlett kernel			Bandwidth: 97 (Newey-West automatic) using Bartlett kernel			Bandwidth: 24 (Newey-West automatic) using Bartlett kernel		
	Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*		Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-159.116	0.0001	Phillips-Perron test statistic	-192.908	0.0001	Phillips-Perron test statistic	36.758	1
Test critical values:			Test critical values:			Test critical values:		
1% level	-2.565		1% level	-2.565		1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		

EWU

Null Hypothesis: ALL_DISC has a unit root

Exogenous: None

Bandwidth: 127 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-290.572	0.0001
Test critical values: 1% level	-2.565	
5% level	-1.941	
10% level	-1.617	

*MacKinnon (1996) one-sided p-values.

Appendix Table 12: Phillips-Perron Test Results for Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

IVV	EWC		EWV		EWV			
Null Hypothesis: ALL_DISC has a unit root	Null Hypothesis: ALL_DISC has a unit root		Null Hypothesis: ALL_DISC has a unit root		Null Hypothesis: ALL_DISC has a unit root			
Exogenous: None	Exogenous: None		Exogenous: None		Exogenous: None			
Bandwidth: 153 (Newey-West automatic) using Bartlett kernel	Bandwidth: 165 (Newey-West automatic) using Bartlett kernel		Bandwidth: 134 (Newey-West automatic) using Bartlett kernel		Bandwidth: 134 (Newey-West automatic) using Bartlett kernel			
	Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*	Adj. t-Stat	Prob.*		
Phillips-Perron test statistic	-343.048	0.0001	Phillips-Perron test statistic	-317.528	0.0001	Phillips-Perron test statistic	-355.150	0.0001
Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565		Test critical values: 1% level	-2.565	
5% level	-1.941		5% level	-1.941		5% level	-1.941	
10% level	-1.617		10% level	-1.617		10% level	-1.617	
*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.			*MacKinnon (1996) one-sided p-values.		

EWZ

Null Hypothesis: ALL_DISC has a unit root

Exogenous: None

Bandwidth: 126 (Newey-West automatic) using Bartlett kernel

	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-338.188	0.0001
Test critical values: 1% level	-2.565	
5% level	-1.941	
10% level	-1.617	

*MacKinnon (1996) one-sided p-values.

B.3 KPSS Test Statistics

Appendix Table 13: KPSS Test Results for Non-Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

EWA		EWH		EWJ	
Null Hypothesis: ALL_DISC is stationary		Null Hypothesis: ALL_DISC is stationary		Null Hypothesis: ALL_DISC is stationary	
Exogenous: Constant		Exogenous: Constant		Exogenous: Constant	
Bandwidth: 151 (Newey-West automatic) using Bartlett kernel		Bandwidth: 143 (Newey-West automatic) using Bartlett kernel		Bandwidth: 161 (Newey-West automatic) using Bartlett kernel	
	LM-Stat.		LM-Stat.		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	2.986	Kwiatkowski-Phillips-Schmidt-Shin test statistic	4.441	Kwiatkowski-Phillips-Schmidt-Shin test statistic	2.443
Asymptotic critical values*:		Asymptotic critical values*:		Asymptotic critical values*:	
1% level	0.739	1% level	0.739	1% level	0.739
5% level	0.463	5% level	0.463	5% level	0.463
10% level	0.347	10% level	0.347	10% level	0.347
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)	

EWM		EWS		EWT	
Null Hypothesis: ALL_DISC is stationary		Null Hypothesis: ALL_DISC is stationary		Null Hypothesis: ALL_DISC is stationary	
Exogenous: Constant		Exogenous: Constant		Exogenous: Constant	
Bandwidth: 86 (Newey-West automatic) using Bartlett kernel		Bandwidth: 83 (Newey-West automatic) using Bartlett kernel		Bandwidth: 149 (Newey-West automatic) using Bartlett kernel	
	LM-Stat.		LM-Stat.		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	5.094	Kwiatkowski-Phillips-Schmidt-Shin test statistic	4.512	Kwiatkowski-Phillips-Schmidt-Shin test statistic	4.150
Asymptotic critical values*:		Asymptotic critical values*:		Asymptotic critical values*:	
1% level	0.739	1% level	0.739	1% level	0.739
5% level	0.463	5% level	0.463	5% level	0.463
10% level	0.347	10% level	0.347	10% level	0.347
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)	
EWY					
Null Hypothesis: ALL_DISC is stationary					
Exogenous: Constant					
Bandwidth: 148 (Newey-West automatic) using Bartlett kernel					
	LM-Stat.				
Kwiatkowski-Phillips-Schmidt-Shin test statistic	3.967				
Asymptotic critical values*:					
1% level	0.739				
5% level	0.463				
10% level	0.347				
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)					

Appendix Table 14: KPSS Test Results for Partially Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

EWD			EWG			EWI		
Null Hypothesis: ALL_DISC is stationary			Null Hypothesis: ALL_DISC is stationary			Null Hypothesis: ALL_DISC is stationary		
Exogenous: Constant			Exogenous: Constant			Exogenous: Constant		
Bandwidth: 115 (Newey-West automatic) using Bartlett kernel			Bandwidth: 104 (Newey-West automatic) using Bartlett kernel			Bandwidth: 129 (Newey-West automatic) using Bartlett kernel		
		LM-Stat.			LM-Stat.			LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		3.872	Kwiatkowski-Phillips-Schmidt-Shin test statistic		2.376	Kwiatkowski-Phillips-Schmidt-Shin test statistic		1.895
Asymptotic critical values*:	1% level	0.739	Asymptotic critical values*:	1% level	0.739	Asymptotic critical values*:	1% level	0.739
	5% level	0.463		5% level	0.463		5% level	0.463
	10% level	0.347		10% level	0.347		10% level	0.347
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		
EWK			EWL			EWN		
Null Hypothesis: ALL_DISC is stationary			Null Hypothesis: ALL_DISC is stationary			Null Hypothesis: ALL_DISC is stationary		
Exogenous: Constant			Exogenous: Constant			Exogenous: Constant		
Bandwidth: 55 (Newey-West automatic) using Bartlett kernel			Bandwidth: 147 (Newey-West automatic) using Bartlett kernel			Bandwidth: 62 (Newey-West automatic) using Bartlett kernel		
		LM-Stat.			LM-Stat.			LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		2.432	Kwiatkowski-Phillips-Schmidt-Shin test statistic		3.951	Kwiatkowski-Phillips-Schmidt-Shin test statistic		3.514
Asymptotic critical values*:	1% level	0.739	Asymptotic critical values*:	1% level	0.739	Asymptotic critical values*:	1% level	0.739
	5% level	0.463		5% level	0.463		5% level	0.463
	10% level	0.347		10% level	0.347		10% level	0.347
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		
EWO			EWP			EWQ		
Null Hypothesis: ALL_DISC is stationary			Null Hypothesis: ALL_DISC is stationary			Null Hypothesis: ALL_DISC is stationary		
Exogenous: Constant			Exogenous: Constant			Exogenous: Constant		
Bandwidth: 75 (Newey-West automatic) using Bartlett kernel			Bandwidth: 93 (Newey-West automatic) using Bartlett kernel			Bandwidth: 103 (Newey-West automatic) using Bartlett kernel		
		LM-Stat.			LM-Stat.			LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		1.143	Kwiatkowski-Phillips-Schmidt-Shin test statistic		1.809	Kwiatkowski-Phillips-Schmidt-Shin test statistic		2.118
Asymptotic critical values*:	1% level	0.739	Asymptotic critical values*:	1% level	0.739	Asymptotic critical values*:	1% level	0.739
	5% level	0.463		5% level	0.463		5% level	0.463
	10% level	0.347		10% level	0.347		10% level	0.347
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)			*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		

EWU

Null Hypothesis: ALL_DISC is stationary

Exogenous: Constant

Bandwidth: 104 (Newey-West automatic) using Bartlett kernel

	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	3.723
Asymptotic critical values*:	
1% level	0.739
5% level	0.463
10% level	0.347

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Appendix Table 15: KPSS Test Results for Synchronous ETPs - Jan 2006 to Jul 2014 - Aggregated Data

IVV		EWC		EWV	
Null Hypothesis: ALL_DISC is stationary		Null Hypothesis: ALL_DISC is stationary		Null Hypothesis: ALL_DISC is stationary	
Exogenous: Constant		Exogenous: Constant		Exogenous: Constant	
Bandwidth: 158 (Newey-West automatic) using Bartlett kernel		Bandwidth: 84 (Newey-West automatic) using Bartlett kernel		Bandwidth: 136 (Newey-West automatic) using Bartlett kernel	
	LM-Stat.		LM-Stat.		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	2.179	Kwiatkowski-Phillips-Schmidt-Shin test statistic	3.152	Kwiatkowski-Phillips-Schmidt-Shin test statistic	4.112
Asymptotic critical values*:		Asymptotic critical values*:		Asymptotic critical values*:	
1% level	0.739	1% level	0.739	1% level	0.739
5% level	0.463	5% level	0.463	5% level	0.463
10% level	0.347	10% level	0.347	10% level	0.347
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)		*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)	
EWZ					
Null Hypothesis: ALL_DISC is stationary					
Exogenous: Constant					
Bandwidth: 127 (Newey-West automatic) using Bartlett kernel					
	LM-Stat.				
Kwiatkowski-Phillips-Schmidt-Shin test statistic	5.247				
Asymptotic critical values*:					
1% level	0.739				
5% level	0.463				
10% level	0.347				
*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)					

Appendix C

Appendix Table 16: Descriptive Statistics for Partially Synchronous ETPs - 11:00am to 11:15am

	Sweden	Germany	Italy	Belgium	Switzerland	Netherlands	Austria	Spain	France	United Kingdom
Ticker	EWD	EWG	EWI	EWK	EWL	EWN	EWO	EWP	EWQ	EWU
Mean	-13.18	-12.96	-13.25	-13.89	-13.70	-14.05	-13.75	-13.20	-13.43	-13.15
Median	-13.01	-12.94	-13.08	-13.60	-13.56	-13.82	-13.47	-13.05	-13.27	-13.14
Maximum	-8.12	-8.19	-8.47	-7.05	-7.84	-7.13	-8.16	-8.26	-8.08	-8.68
Minimum	-27.20	-19.78	-27.68	-27.12	-27.11	-27.12	-27.62	-28.51	-27.65	-25.42
Std. Dev.	1.65	1.30	1.75	2.26	1.77	2.04	2.07	1.60	1.65	1.35
Skewness	-1.03	-0.08	-1.26	-1.76	-1.67	-1.52	-1.91	-1.47	-1.17	-0.47
Kurtosis	7.14	4.08	8.88	10.42	13.01	9.94	11.78	11.37	8.85	6.83
Observations	2 049	2 143	1 832	1 387	2 057	1 655	1 734	2 028	1 965	2 134

Appendix Table 17: Results of Wilcoxon Signed Rank Test for Partially Synchronous ETPs - 11:00am to 11:15am compared with 11:15am to 11:30am

Hypothesis Testing for EWD				Hypothesis Testing for EWG				Hypothesis Testing for EWI			
Included observations: 2036				Included observations: 2141				Included observations: 1829			
Test of Hypothesis: Median = -13.00506				Test of Hypothesis: Median = -12.93803				Test of Hypothesis: Median = -13.08127			
Sample Median = -13.18799				Sample Median = -13.13627				Sample Median = -13.19373			
Method	Value	Probability		Method	Value	Probability		Method	Value	Probability	
Wilcoxon signed rank	6.658802	0.00%		Wilcoxon signed rank	6.426959	0.00%		Wilcoxon signed rank	5.736851	0.00%	
Median Test Summary				Median Test Summary				Median Test Summary			
Category	Count	Mean Rank		Category	Count	Mean Rank		Category	Count	Mean Rank	
Obs > -13.00506	908	947.3293	46.53%	Obs > -12.93803	926	1039.571	48.56%	Obs > -13.08127	852	830.0164	45.38%
Obs < -13.00506	1128	1075.79	52.84%	Obs < -12.93803	1215	1094.953	51.14%	Obs < -13.08127	977	989.1105	54.08%
Obs = -13.00506	0			Obs = -12.93803	0			Obs = -13.08127	0		

Hypothesis Testing for EWK				Hypothesis Testing for EWL			
Included observations: 1383				Included observations: 2055			
Test of Hypothesis: Median = -13.59708				Test of Hypothesis: Median = -13.55531			
Sample Median = -13.52582				Sample Median = -13.66719			
Method	Value	Probability		Method	Value	Probability	
Wilcoxon signed rank	1.080666	0.280		Wilcoxon signed rank	3.778651	0.02%	
Median Test Summary				Median Test Summary			
Category	Count	Mean Rank		Category	Count	Mean Rank	
Obs > -13.59708	710	651.3577	47.10%	Obs > -13.55531	975	979.0933	47.64%
Obs < -13.59708	673	734.8767	53.14%	Obs < -13.55531	1080	1072.152	52.17%
Obs = -13.59708	0			Obs = -13.55531	0		

Hypothesis Testing for EWN			Hypothesis Testing for EWO			Hypothesis Testing for EWP					
Included observations: 1583			Included observations: 1737			Included observations: 2033					
Test of Hypothesis: Median = -13.81728			Test of Hypothesis: Median = -13.47002			Test of Hypothesis: Median = -13.04630					
Sample Median = -13.92976			Sample Median = -13.47741			Sample Median = -13.19543					
Method	Value	Probability	Method	Value	Probability	Method	Value	Probability			
Wilcoxon signed rank	4.730553	0.00%	Wilcoxon signed rank	2.476798	1.33%	Wilcoxon signed rank	6.594533	0.00%			
Median Test Summary			Median Test Summary			Median Test Summary					
Category	Count	Mean Rank	Category	Count	Mean Rank	Category	Count	Mean Rank			
Obs > -13.81728	735	735.8068	46.48%	Obs > -13.47002	866	811.7125	46.73%	Obs > -13.04630	907	947.3142	46.60%
Obs < -13.81728	848	840.7052	53.11%	Obs < -13.47002	871	925.9587	53.31%	Obs < -13.04630	1126	1073.132	52.79%
Obs = -13.81728	0			Obs = -13.47002	0			Obs = -13.04630	0		

Hypothesis Testing for EWQ			Hypothesis Testing for EWU		
Included observations: 1976			Included observations: 2136		
Test of Hypothesis: Median = -13.27437			Test of Hypothesis: Median = -13.13868		
Sample Median = -13.49999			Sample Median = -13.16115		
Method	Value	Probability	Method	Value	Probability
Wilcoxon signed rank	8.213997	0.00%	Wilcoxon signed rank	0.199331	84.20%
Median Test Summary			Median Test Summary		
Category	Count	Mean Rank	Category	Count	Mean Rank
Obs > -13.27437	859	894.3888	Obs > -13.13868	1052	1079.349
Obs < -13.27437	1117	1060.874	Obs < -13.13868	1084	1057.971
Obs = -13.27437	0		Obs = -13.13868	0	

Appendix Table 18: Descriptive Statistics Partially Synchronous ETPs - 11:30am to 11:45am

Market	Sweden	Germany	Italy	Belgium	Switzerland	Netherlands	Austria	Spain	France	United Kingdom
Ticker	EWD	EWG	EWI	EWK	EWL	EWN	EWO	EWP	EWQ	EWU
Mean	-13.60	-13.59	-13.74	-14.13	-14.04	-14.39	-13.91	-13.68	-14.09	-13.63
Median	-13.45	-13.63	-13.56	-13.78	-13.98	-14.19	-13.66	-13.57	-13.92	-13.61
Maximum	-8.64	-8.20	-9.05	-8.07	-9.11	-9.15	-7.04	-9.16	-8.99	-7.10
Minimum	-27.61	-22.57	-25.32	-26.88	-27.12	-26.95	-27.65	-28.10	-27.77	-26.70
Std. Dev.	1.71	1.41	1.75	2.31	1.73	1.99	2.14	1.67	1.81	1.49
Skewness	-1.11	-0.15	-0.79	-1.66	-0.60	-1.09	-1.49	-1.93	-1.23	-0.85
Kurtosis	8.44	4.61	5.06	8.69	5.26	7.46	9.56	15.25	8.94	9.41
Observations	2 019	2 142	1 747	1 303	1 999	1 525	1 670	1 993	1 919	2 112

Appendix Table 19: Results of Wilcoxon Signed Rank Test for Partially Synchronous ETPs - 11:30am to 11:45am compared with 11:45am to 12:00pm

Hypothesis Testing for EWD				Hypothesis Testing for EWG				Hypothesis Testing for EWI			
Included observations: 2017				Included observations: 2143				Included observations: 1805			
Test of Hypothesis: Median = -13.45105				Test of Hypothesis: Median = -13.62830				Test of Hypothesis: Median = -13.56348			
Sample Median = -13.12493				Sample Median = -13.24529				Sample Median = -13.06859			
Method	Value	Probability		Method	Value	Probability		Method	Value	Probability	
Wilcoxon signed rank	6.33260989	0.00%		Wilcoxon signed rank	14.1648363	0.00%		Wilcoxon signed rank	9.91469297	0.00%	
Median Test Summary				Median Test Summary				Median Test Summary			
Category	Count	Mean Rank		Category	Count	Mean Rank		Category	Count	Mean Rank	
Obs > -13.45105	1177	1005.29737	49.84%	Obs > -13.62830	1335	1164.37678	54.33%	Obs > -13.56348	1124	920.403915	50.99%
Obs < -13.45105	840	1014.1881	50.28%	Obs < -13.62830	808	919.372525	42.90%	Obs < -13.56348	681	874.274596	48.44%
Obs = -13.45105	0			Obs = -13.62830	0			Obs = -13.56348	0		

Hypothesis Testing for EWK				Hypothesis Testing for EWL				Hypothesis Testing for EWN			
Included observations: 1357				Included observations: 2037				Included observations: 1546			
Test of Hypothesis: Median = -13.78441				Test of Hypothesis: Median = -13.97745				Test of Hypothesis: Median = -14.18538			
Sample Median = -13.41681				Sample Median = -13.50323				Sample Median = -13.73076			
Method	Value	Probability		Method	Value	Probability		Method	Value	Probability	
Wilcoxon signed rank	5.66662	0.00%		Wilcoxon signed rank	13.8678	0.00%		Wilcoxon signed rank	7.780318	0.00%	
Median Test Summary				Median Test Summary				Median Test Summary			
Category	Count	Mean Rank		Category	Count	Mean Rank		Category	Count	Mean Rank	
Obs > -13.78441	787	689.3506	50.80%	Obs > -13.9774	1295	1085.741	53.30%	Obs > -14.18538	958	766.7119	49.59%
Obs < -13.78441	570	664.7087	48.98%	Obs < -13.9774	742	902.517	44.31%	Obs < -14.18538	588	784.559524	50.75%
Obs = -13.78441	0			Obs = -13.9774	0			Obs = -14.18538	0		

Hypothesis Testing for EWO				Hypothesis Testing for EWP				Hypothesis Testing for EWQ			
Included observations: 1755				Included observations: 2029				Included observations: 1949			
Test of Hypothesis: Median = -13.65772				Test of Hypothesis: Median = -13.57462				Test of Hypothesis: Median = -13.92304			
Sample Median = -13.13770				Sample Median = -12.96897				Sample Median = -13.40151			
Method	Value	Probability		Method	Value	Probability		Method	Value	Probability	
Wilcoxon signed rank	9.47547	0.00%		Wilcoxon signed rank	16.5382	0.00%		Wilcoxon signed rank	14.0855	0.00%	
Median Test Summary				Median Test Summary				Median Test Summary			
Category	Count	Mean Rank		Category	Count	Mean Rank		Category	Count	Mean Rank	
Obs > -13.65772	1095	887.3406	50.56%	Obs > -13.57462	1371	1069.450	52.71%	Obs > -13.92304	1282	1014.148	52.03%
Obs < -13.65772	660	862.5030	49.15%	Obs < -13.57462	658	901.5486	44.43%	Obs < -13.92304	667	899.7556	46.16%
Obs = -13.65772	0			Obs = -13.57462	0			Obs = -13.92304	0		

Hypothesis Testing for EWP				Hypothesis Testing for EWQ				Hypothesis Testing for EWU			
Included observations: 2029				Included observations: 1949				Included observations: 2117			
Test of Hypothesis: Median = -13.57462				Test of Hypothesis: Median = -13.92304				Test of Hypothesis: Median = -13.61175			
Sample Median = -12.96897				Sample Median = -13.40151				Sample Median = -13.12926			
Method	Value	Probability		Method	Value	Probability		Method	Value	Probability	
Wilcoxon signed rank	16.5382	0.00%		Wilcoxon signed rank	14.0856	0.00%		Wilcoxon signed rank	17.2349	0.00%	
Median Test Summary				Median Test Summary				Median Test Summary			
Category	Count	Mean Rank		Category	Count	Mean Rank		Category	Count	Mean Rank	
Obs > -13.57462	1371	1069.45	52.71%	Obs > -13.92304	1282	1014.15	52.03%	Obs > -13.61175	1398	1148.6	54.26%
Obs < -13.57462	658	901.549	44.43%	Obs < -13.92304	667	899.756	46.16%	Obs < -13.61175	719	884.787	41.79%
Obs = -13.57462	0			Obs = -13.92304	0			Obs = -13.61175	0		