AN EMPIRICAL EXAMINATION OF THE STOCK RETURN DYNAMICS OF DEVELOPED, EMERGING AND FRONTIER MARKETS

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Abstract

This thesis is comprised of three chapters that independently investigate the dynamics of market efficiency, market integration, portfolio diversification and risk management of developed, emerging and frontier equity markets. Overall, we have demonstrated that market efficiency, market integration, asset portfolio allocation and hedging effectiveness vary continuously over time and across markets due to changing economic conditions.

In chapter one, we examine the return predictability and technical trading rules profitability of developed, emerging and frontier equity markets over the period 1999 to 2015. Using automatic portmanteau test and wild bootstrapped automatic variance ratio test, we find evidence of time-varying return predictability to be consistent with the adaptive market hypothesis. Secondly, we find that the adaptive moving average rule outperforms the moving average convergence-and-divergence rule and buy-and-hold strategy on the basis of dynamic profitability and risk-adjusted profits. Finally, we find that macroeconomic volatility weakly increases technical rule profitability while crisis period strongly diminishes profitability.

In chapter two, we evaluate the spillover effects, correlation dynamics and macro-finance determinants between UK and US stock markets for a long dataset using asymmetric BEKK-GARCH model. We carry out empirical analysis by splitting the period 1935 – 2015 into Interwar/Second World War, Bretton Wood System, pre-UK exchange control, post-UK exchange control, pre-EMU and post-EMU, and find that shock and asymmetric volatility spillovers have become stronger in the final period between the two markets, suggesting strong financial linkages. Using mixed-sampling regression model, we find that stock market integration has been driven by macroeconomic convergences, financial indicators, stock market characteristics and market contagion.

In chapter three, we examine correlation dynamics, portfolio diversification and risk management of developed, emerging and frontier equity markets from 1999 to 2015 using asymmetric BEKK-GARCH and value-at-risk models. We find that with very low integration, strong hedging effectiveness, significantly high portfolio returns and minimal loss of investment, UK investors are better-off holding diversified portfolios that include UK and frontier markets during the Great Moderation period (1999 – 2007). In contrast, as a result of moderately high integration, less strong hedging effectiveness, comparatively low tail risk and marginally high portfolio returns and relatively lower loss of investment, UK investors are better off holding two-asset portfolio that include UK and some emerging and frontier markets during the Great Austerity period (2007 – 2015).

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Research Background

Over the past five decades, there has been an increasing interest in investigating the theoretical and empirical basis for Efficient Market Hypothesis (EMH). Generally, the EMH is underpinned by the principle of rationality with an implication that the activities of competing market participants will cause a fully accurate and instantaneous incorporation of all available information into actual pricing of a financial asset (see Fama, 1965, 1970). By contrast, the behavioural finance theorists' document the violations of market rationality on the basis of behavioural biases exhibited by economic agents in decision making under uncertainty (see Kahneman and Tversky, 1982; De Bondt and Thaler, 1985, Dissanaike, 1997; Barber and Odean, 2001). Some of the prevailing market imperfections attributed to behavioural biases in investment decisions include loss aversion, overconfidence, underreaction, overreaction, momentum effect, herding behaviour and sentiment.

In order to reconcile the efficient market with behavioural finance, Lo (2004) describes a new market framework from an evolutionary perspective, called the Adaptive Market Hypothesis (AMH). In rapidly changing economic conditions, the instantaneous adjustment of market prices may seem untenable as a result of market imperfections arising from information inefficiency. Therefore, the evolutionary nature of the market creates profit opportunities which may be exploited and eroded as financial market players learn to take advantage of them. An important implication of the AMH is that market efficiency varies continuously over time and across markets due to changing market conditions (see Lo, 2005; Kim *et al.,* 2011; Urquhart and Hudson, 2013). Fundamentally, the evolutionary principles underpinning AMH can explain complex market dynamics, going through the cycles of bubbles and busts, expansions and contractions, which are common phenomena in natural market ecologies (see Lo, 2004; 2005). The fact that the performance of investment strategies, including fundamental and technical analysis can perform well in certain market environments and poorly in others, suggests that investors may potentially arbitrage and exploit profit opportunities due to unstable risk-return relationship over time.

However, there has been longstanding debate between professional investors' belief in making considerable profits by predicting market returns and large swathes of academics' position on the unpredictability of market returns. The reality is that the predictability of future returns based on historical information is fraught with dangers of huge investment losses particularly, if negative shocks hit the financial markets. As a result, professional traders would select the most profitable trading system that perform optimally in terms of eliminating the losses due to price shocks and perhaps make gains from their investment strategies. This is why comparing the performance of the trend-following systems capable of generating trading profit is crucial for investors and financial analysts. Despite financial markets being driven by economic fundamentals, most professional traders use both fundamental and technical analysis to determine the short-term direction of market prices.

It will be naïve for investors to think that a trading strategy that identifies a profit opportunity is risk-free. It is also inconceivable to conclude that return predictability can be economically exploited without taking into account transactions costs, taxes and other related costs. In any case, the use of technical analysis has a long history among practitioners particularly to speculate on profit opportunities in the markets. It is therefore critical for investors to evaluate profitability of technical trading strategies on a risk-adjusted basis in order to account for systematic and non-systematic risks. Primarily, investors can minimise non-systematic risk through diversification, while systematic risk can be mitigated through hedging or appropriate asset allocation strategies.

It is equally important to argue that the application of the AMH framework would have important implications on price discovery, market integration, financial contagion, asset allocation, portfolio diversification and risk management. Moreover, there is a plausible connection between the degree of market efficiency and market integration. We conjecture that markets with higher degree of efficiency are more likely to have stronger integration between them. The reason being that a risk-averse investor may potentially diversify more into markets with less market imperfections and frictions, hence increasing market integration. In like manner, market efficiency may improve by fundamentally reducing portfolio home bias of investors in a growing integration markets.

The integration of financial markets has been broadly defined in the context of financial openness, unrestricted capital flows, integration of financial services and macroeconomic convergence. The openness of economies to trade and surge in international capital outflows have contributed to growing financial integration in the world, particularly among developed countries. Likewise, the process of globalisation is leading to the integration of economies, industries, markets and policy-making around the world. In fact, the level of interaction between macroeconomic fundamentals and financial stability is dynamically affecting policy-making and regulatory framework.

Since the Great Depression, unexpected events and shocks have introduced significant volatility and uncertainty into the financial markets. Particularly, asset price shocks are usually accompanied by high volatility. Hence, the growing financial integration is also evident by the level of transmission of shocks from one financial centre to the rest of the world with close immediate reactions. A recent example is the 2008 stock market crash triggered by the collapse of the fourth largest investment banks (Lehman Brothers Inc.) in the US, led to economic crisis of her more influential trading partners in Europe, America and Asia. It is undoubtedly evident that the turbulence in the global economy is increasing volatility and uncertainty in an increasingly globalised financial markets. Therefore, the levels of shock and volatility transmissions from one country to another may contribute significantly to increasing financial market integration.

Over time, recurrent economic changes have altered asset price relationships. For instance, countries have abolished capital and exchange controls for improved financial development; floated their currencies, opened up their capital markets and promoted financial liberalisation; joined trade and monetary union to facilitate economic integration etc. For each of these events, there has been an alteration in price patterns, perhaps more or less volatile sometimes, and may also have influenced the degree of financial integration between developed and developing markets.

Furthermore, the effects of price shocks either caused by a structural change (i.e. permanent price shift) or unexpected temporal change (e.g. Central Banks announcements, regulatory changes, corporate earnings announcements, periodic reports of unemployment rates, consumer confidence, geopolitical factors, weather-related news, natural disasters etc.) may impact financial markets stability. As a consequence, the inconsistency of macroeconomic policies with financial stability could fundamentally lead to a decline in financial market integration as a result of global financial market uncertainty, asset price misalignments and divergence in investors' sentiment. In a bid to mitigate exposure to market risks, investors commonly adopt the strategy of portfolio diversification.

Generally, diversification is the ideal method of risk reduction if portfolio assets are uncorrelated. The primary aim of international diversification is to enhance the risk-return benefit for investors. As an example, when two stock indices have the same returns, a risk-averse investor will choose the index with the lowest risk. Likewise, an investor will choose a stock index with the highest stock returns when two stock indices have the same risk. Nevertheless, more risk reduction is gained when correlation between assets is low, hence country-specific risk or non-systematic risk can be minimised with international diversification.

A matter of great concern for investors is that portfolio diversification is more difficult when financial markets are integrating rapidly. Therefore, investors may seek to diversify to markets with less integration thereby improving their diversification opportunities. Even though there has been increased in cross-border stock holdings, the tendency for investors to hold a disproportionately share of domestic assets in their portfolio is quiet substantial, thus utmost gains from international diversification is minimised. This puzzle in *portfolio choice theory* is popularly referred to as *equity home bias*. The presence of market frictions is cited as evidence in support of *equity home bias,* which include; transaction costs, asymmetric information, portfolio constraints, regulatory barriers and other market imperfections.

Expectedly, market efficiency should improve if portfolio home bias of investors is reduced in a growing integrated financial markets. Consider as an illustration, if investors in search of higher returns with lower risk shift investment to markets that are less efficient, then intense trading activities will compete away the profit opportunities, hence the markets become more efficient and integrated over time. In tackling this portfolio allocation problem, investors may seek to hedge their overexposure to domestic risk by using foreign stock markets for instance to hedge against adverse price movement, hence reducing systematic or market risk. Accordingly, portfolio allocation decisions and risk-minimising hedging strategies are worth investigating in order to improve our understanding of strategic portfolio management.

In a similar vein, improving profits and assessing market risks have become complicated for many investors in a rapidly changing financial markets. In order to quantify market risk accurately, risk managers consider the use of risk management models such as the value-at-risk measure. The recent global financial crisis reveals the billions of dollars lost by investors as a result of inadequate supervision and management of market risk. Consequently, the exposure of investors to market risk has given more impetus to the growing importance of risk management models. In recent times, risk managers use backtesting procedures of market risk estimation to choose the appropriate model for the estimation and to ascertain the accuracy of downside risk of portfolio investment. The quantification of market risk of diversified portfolios has several important implications for international diversification.

Against this background, this thesis broadly investigates the stock return dynamics of developed, emerging and frontier markets. From the perspective of a UK investor, we use daily stock indices to examine the dynamics of market efficiency, price discovery, market integration, international diversification and risk management in rapidly changing economic environments. Essentially, the evolution of stock market integration basically depends on the phase of development and liquidity of the financial markets, hence the categorisation into developed, emerging and frontier markets. However, there is limited research on the fundamental aspects of stock return dynamics from the perspective of the UK investors despite London's ranking as first in 'Global Financial Centre Index' and UK's well-developed financial architecture. There are similarly few studies that examine stock return dynamics in an internationally diverse context, particularly in comparative terms among the three classification of markets.

This thesis is comprised of three chapters that separately investigate market efficiency, market integration and risk diversification of developed, emerging and frontier markets. For robustness and comparative analysis, the first and third chapters with a sample period from 1999 to 2015 are divided into two equal subsamples, namely; the 'Great Moderation' (1999 – 2007) characterised as a period of tranquillity in the international macroeconomic environment and, the 'Great Austerity' (2007 – 2015) identified as a period of turbulence in the international macroeconomic environment. These subsamples help to capture investors' reactions in reassessing the dynamic nature of portfolio risks, returns, holdings and hedging, particularly when financial and economic vulnerabilities gather momentum in the international market.

Equally important, the second chapter with sample period from 1935 to 2015 is partitioned into six subsamples, namely; the Interwar/Second World War (1935 – 1945); the Bretton Woods System of Fixed exchange rate regime (1945 – 1971); the Pre-1979 UK Exchange controls (1971 – 1979); the Post-1979 UK Exchange controls (1979 – 1990); the Pre-European Monetary Union (1990 – 1999) and the Post-European Monetary Union (1999 – 2015). The importance of the subsample analysis is to enhance the understanding of both short- and long-term dynamics of the financial markets, which would yield more detailed picture as to how the evolving international financial architecture underscores the changing sensitivity of financial markets to macroeconomic news and innovations.

To our knowledge, these chapters are the first to consider the uniqueness of these subsamples in understanding the dynamics of market efficiency, financial integration, portfolio diversification and risk management for a large selection of developed, emerging and frontier equity markets. Unlike the EMH framework that measures absolute efficiency, we lean more towards the AMH framework which provides a useful benchmark for measuring relative efficiency. Following this, the adaptability to changing market conditions indicates that investors have the capacity to construct an optimal dynamic asset allocation and hedging effectiveness. These chapters also fill the gaps of the limited and inconclusive empirical evidence in understanding dynamically the financial linkages between UK and the rest of the world (that is, mature and immature markets).

In conclusion, this thesis has several salient policy implications that are relevant to risk managers, portfolio managers, institutional investors, policy-makers and researchers. From the investors' perspective, it is important to understand the nature of market efficiency and the role of market integration to properly construct optimal asset allocation, design effective hedging strategy and quantify appropriate the market risk. From the policymakers' perspective, it is important to understand the role of shocks and volatility spillovers, as well as drivers of financial integration in order to appropriately calibrate their policy response.

Chapter 1. Market Efficiency of Developed, Emerging and Frontier Equity Markets: Evidence from Return Predictability Measures and Technical Trading Rules

1.1 Introduction

The efficient market hypothesis (EMH) remains a fundamental theory in finance since its postulation by Fama (1965a, 1965b, 1970) and Samuelson (1965). The EMH was triggered by the empirical evidence provided by Alexander in 1961 that utilising filter rules will yield profitability in stock market trading. The alternative to technical analysis is fundamental analysis but most fund managers prefer using the former because of the predictive power of technical trading rules (see, Menkhoff, 2010). However, technical analysis provides information on non-fundamental impact on stock price movements. As a consequence, the performance of technical analysis as a measure of market efficiency has been further scrutinised by academics and practitioners.

In general, the EMH states that market is informationally efficient because all available information is fully and immediately incorporated in the pricing of a security.[1] That is to say, price cannot be predicted based on technical trading rules applied to historical prices, therefore making abnormal profit practically impossible for market participants. The financial market is assumed to be perfect and financial returns generated cannot be predicted by any rational economic agents. This further implies that market prices follow a random walk which satisfies the weak-form market efficiency.

Subsequently, the validity of EMH is being challenged both theoretically and empirically. A theoretical plausible argument by Grossman and Stiglitz (1976, 1980), debunked the possibility of perfectly efficient market on the basis that traders would not have an inducement to procure costly information if prices fully incorporate all available information. Another twist to this argument is the evidence provided by Chan *et al*. (1996), that financial markets do not process information instantaneously as described by EMH. According to Mukherjee *et al*. (2011), for long memory in financial time series, the market does not immediately react to new information as the EMH suggests, but instead responds to such information gradually over a period of time. These positions support the noisy rational expectation models that current market price does not fully reflect all available information because of unpredictable price movements and price shocks caused by noise trading. This corroborates with many active investors' view that the

[1] Fama (1965, p. 56) states that "in an efficient market, however, the actions of the many competing participants should cause the actual price of a security to wander randomly about its intrinsic value."

attraction for abnormal returns is the basis for engaging in portfolio investment and they would therefore seek every available information to realise this fundamental objective.

According to Ratner and Leal (1999), predictability does not imply inefficiency if the application of a known trading strategy does not generate systematic economic gains to its users. Does it then mean that the market is still efficient if return predictability cannot be exploited profitably? Perhaps, the predictable returns may not be economically exploited due to transaction costs, taxes and institutional rigidities. According to Brown (2008), predictability is neither a necessary nor a sufficient condition to establish profitability of a trading strategy. Therefore, developing a systematic trading strategy based on the degree of market efficiency will shed more light on profitability.

The behavioural economists have been the most critical of the EMH paradigm, providing theoretical and empirical perspectives inconsistent with the EMH. For instance, there is a growing evidence about market imperfections which can be attributed to behavioural biases such as under-reaction (Chan *et al*., 1996), overreaction (Kahneman and Tversky, 1982; De Bondt and Thaler, 1985, Dissanaike, 1997), overconfidence (Barber and Odean, 2001), greed and fear (Kahneman and Tversky, 1979), loss aversion (Kahneman and Tversky, 1979; Odean, 1998), herding (Huberman and Regev, 2001). Other criticisms of EMH include, market anomalies arising from market bubbles, market crashes, calendar effect, day-of-the-week effect and size effect (Banz, 1981; Keim, 1983; Opong *et al.*, 1999; Schleifer, 2000; Lo and Mackinlay, 2001; Shiller, 2003). Most of these behavioural economics studies are underpinned by Simon's notion of bounded rationality (Simon, 1955) rather than the unbounded or perfect rationality used as a basis for explaining market efficiency.[2]

In a bid to bridge the gap between the proponents of EMH and behavioural economics, Lo (2004, 2005) uses evolutionary principles to produce a new framework called the adaptive market hypothesis (AMH). According to Lo (2004), the degree of market efficiency caused by environmental factors are underpinned by market ecology such as number of market competitors, extent of availability of profit opportunities and the adaptability of market players. This implies that the AMH accommodates the behavioural biases and market imperfections given that bounded rational agents learn and adapt to changing market conditions. Any shocks to the process of competition and natural selection generate inefficient market but agents' capacity to learn fast will bring efficiency of financial market to the pre-shock levels. Therefore,

[2] Humans do not possess the information or the methodology to constantly optimise in a rational way, and therefore make use of some rules of thumb or heuristics to find satisfactory results that are not necessarily rational (Simon, 1955).

tests of return predictability need to be able to capture the expected changes in market efficiency given that it is not an 'all-or-none condition' but rather a feature that varies continuously over time and across markets.

There seems to be a philosophical belief amongst many academics, practitioners and policy-makers that the markets rationally price assets and risk (that is, free markets are the best way to allocate resources) which explains the dominance of the neo-classical financial paradigm (see Soufian *et al*., 2014). This presupposes that market efficiency may lead to efficient allocation of scarce capital resources. In recent times, the increasing level of investors' exuberance is impeding the degree of market efficiency. Besides, there is a growing criticism about the self-correcting and self-regulating capacity of markets implied by EMH, which some analysts have attributed to be responsible for the recent global financial crisis (see Soros 2008; Volcker, 2011; Fox, 2011). Indeed, the periodic occurrence of financial crises and market crashes may contribute to market inefficiency and these episodes have given policy-makers the impetus to regulate activities in the stock market in order to maintain overall financial market stability. Perhaps, the wide criticisms of EMH as a basis for articulating public policy will shift attention to AMH as a credible alternative source of direction.

In contrast to EMH, the AMH allows for return predictability which can occur from time to time because of changing market conditions. The implication of AMH has been summarised in two perspectives: first, market efficiency is not an all-or-nothing condition but rather a feature that varies continuously over time (Campbell *et al*., 1997); second, market efficiency is 'highly context dependent', that is, it is determined by market conditions (Lo, 2004, p. 23). If indeed markets are adaptive rather than follow a random walk, then technical trading strategies may be effective.

Furthermore, the financial markets in the last two decades have been characterised with increasing easy access to information, electronic trading, minimum market frictions and declining transaction costs. In the age of high frequency trading, the use of algorithm trading in the financial markets seemingly process information rapidly and contributes to dynamic asset allocation. The increasing speed of market price movements arising from the intense use of algorithm trading is reducing the profitability of technical trading rules, hence improving market efficiency. In recent times, the focus on technical analysis is switching towards emerging and frontier markets because they are currently being considered as principal alternative sources of portfolio investment opportunities.

An assortment of econometric models have been employed to test stock market efficiency on the basis of past prices, namely; the unit root tests (Narayan, 2005; Ozdemir, 2008; Hasanov, 2009), variance ratio tests (Chang and Ting, 2000; Smith, 2007; Hung *et al*., 2009)[3], non-linearity tests (Hamil *et al*., 2000; Lim and Brooks, 2009; Panagiotidis, 2010), and long memory tests (Barkoulas *et al.* 2000; Kilic, 2004; Kasman *et al*, 2009). The empirical testing of weak-form efficiency is justified on the basis that its rejection further implies the rejection of other higher forms of efficiency (that is, semi-strong and strong form efficiency).

The empirical findings on market efficiency is mixed. Several studies show that markets are not predictable even on the basis of past market prices (see for example, Lo and MacKinlay, 1988; Lo, 1991; Fama and French, 1998; Kim and Singal, 2000a, 2000b; Andersen *et al.*, 2001; Jegadeesh and Titman, 2001; Füss, 2005, Worthington and Higgs, 2005; Moreno and Olmeda, 2007; Lim *et al*., 2008; Borges 2010; Griffin *et al.*, 2010; Mobarek and Fiorante, 2014 etc.). However, some other studies on emerging markets unravel the invalidity of the weak form efficiency (see for example, Rockinger and Urga, 2000; Chang *et al*., 2004; McPherson and Palardy, 2007; Ito and Sugiyma, 2009). Also, the pervasive momentum effect in stock returns similarly challenges the weak-form efficiency (see Fama and French, 1988; Chan *et al*., 1996; Jegadeesh and Titman, 2001).

In this chapter, we analyse time-varying market efficiency using return predictability measures and short-horizon technical trend-following rules for a large selection of developed, emerging and frontier stock markets over the period 1999 - 2015. The sample is partitioned into the periods of 'Great Moderation' (05/03/1999 – 04/03/2007) and 'Great Austerity' (05/03/2007 – 04/03/2015).[4] The period of study chosen enables us to explore the sensitivity of stock market returns to the following major episodes: the internet bubble bust, the 11th September 2001 terrorist attack, the 2007 – 2009 Global financial crisis and the recent Eurozone debt crisis.

Furthermore, the extent to which investors may profitably trade on the levels of dependence or predictability is determined by trading costs and other associated costs. Some studies have indicated that the magnitude of transaction costs in many markets would make trading unprofitable (see for example, Bekaert *et al.*, 1997; Harvey *et al*., 2000; Chang *et al*., 2004; Moreno and Olmeda, 2007). Transaction cost is one of the market frictions impeding market

[3] Fama (1970) argues that large return autocorrelations reflect deviations from random walk pricing which indicates the violations of market efficiency. Subsequent studies highlight causes of return autocorrelation other than mispricing to include time-varying expected returns, non-synchronous trading and microstructure biases (see Lo and MacKinlay, 1988; Boudoukh *et al.* 1994).

[4] The 'Great Moderation' is characterised by low macroeconomic volatility, stable financial system and booming economy whereas the 'Great Austerity' is characterised by high macroeconomic volatility, financial crisis, economic recession and slow recovery (see McConnell and Perez-Quiros, 2000; Bean 2010; Eichengreem, 2014).

efficiency because it could limit informed traders in incorporating all information in asset pricing. However, by assuming frictionless markets, profitability is measured as the ability to use technical trading rules to earn returns in excess of the buy-and-hold trading strategy. By and large, bridging the gap between most academics' support for market efficiency and expertise of professional traders in making systematic profits will continue to generate interesting findings.

Our motivation is to provide new insights into how market efficiency and the performance of technical trading strategies in the developed, emerging and frontier markets have changed over time. The rationale for this investigation is based on the expectation that market efficiency has evolved over the last 16 years due to institutional factors, regulatory changes, psychological biases, market microstructure, noise trading and information technology, which could thereby create profit opportunities to be exploited overtime and across markets.

This study fills the gaps in the literature as it offers broader coverage with respect to market predictability and technical trading rules profitability from the context of more recent data, well diverse markets and comparable methodologies. A small number of studies have compared the wild bootstrapped variance ratio (WBVAR) and automatic portmanteau (AQ) tests as a measure of return predictability for a limited dataset. For instance, Kim *et al.* (2011) and Lim *et al.* (2013) investigate the WBVAR and AQ tests in the US markets. The variance ratio and portmanteau tests are the most popular tests used by market practitioners in practical applications.

Additionally, the short-horizon trend following trading rules: adaptive moving average (AMA) and moving average convergence divergence (MACD) rules have been neglected in empirical literature despite their increasing relevance in portfolio management. In spite of the fact that no existing study has made comparison between these technical trading rules, very few literature has compared one of the trading rules with other similar ones. For example, Ellis and Parbery (2005) consider the AMA and MA rules in 3 developed stock markets in US and Australia; Ülkü and Prodan (2013) examine the MACD and MA rules in 44 national stock market price indexes cutting across developed, emerging and frontier markets; Stankovic *et al.* (2015) evaluate the MACD and EMA rules in 4 emerging markets in the Balkans and Eastern Europe. In addition, very few studies have been done on examining the determinants of technical trading rule profitability. For example, Ülkü and Prodan (2013) investigate the relationship between financial and macroeconomic indicators and trading rule profitability. Similarly, Taylor (2014) examines the impact of financial market conditions and macroeconomic volatility on profitability in US market. None of the existing papers has used both the MACD and AMA trading rules to investigate the drivers of market profitability.

To sum up, empirical literature is still scant on linking time-varying return predictability and technical trading rule profitability to AMH paradigm. Despite the growing interest of investors in emerging and frontier stock markets, little attention has been given to understanding the degree of return predictability and dynamic trading rule profitability from the perspective of AMH framework. This study therefore aims to contribute in understanding deeply the degree of efficiency and price behaviour of these markets, and draw a wider implication for the functioning of financial markets. The study of adaptive or efficient markets is fundamental in portfolio analysis for investors and it will help policymakers to make effective policy and regulatory decisions that will promote financial market stability.

Throughout this chapter, we are motivated to provide answers to the following questions;

1. What is the nature of market efficiency in developed, emerging and frontier equity markets?
2. Can significant profits be exploited from return predictability in the periods of Great Moderation (GM) and Great Austerity (GA)?
3. Does macroeconomic volatility and changing market conditions drive the profitability of technical trading rules?
4. What are the implications on AMH for market practitioners and policymakers?

This chapter provides contributions to the relevant literature in many respects;

1. Previous studies explore the degree of market efficiency for few selected markets (see Kim *et al*., 2011; Lim *et al.*, 2013; Urquhart and Hudson, 2013). We extend our analysis by using WBAVR and AQ tests to compare the degree of market efficiency of the developed, emerging and frontier equity markets. We finally link the empirical results with theoretical framework of AMH because only a handful of studies have considered these methods on a large dataset.
2. Existing studies have not considered in details the implications of an adaptive market as a basis for explaining technical trading rule profitability (see Ellis and Parbery, 2005; Ülkü and Prodan, 2013; Fang *et al*., 2014). We therefore take a broader outlook by applying two short-horizon trend-following rules (AMA and MACD) to demonstrate consistency of these rules to changing profitability over time based on cumulative wealth of investing and further examine if the trading rules significantly outperform the buy-and-hold strategy on a risk-adjusted basis. Apart from Fang *et al.* (2014) that

studied cumulative wealth and risk-adjusted profits of technical trading rule of US stock index - DJIA, to the best of our knowledge, the novelty of this chapter is that we will extend the analysis to 30 equity markets.

3. Ülkü and Prodan (2013) and Taylor (2014) examine the factors driving the profitability of technical rules. Based on the AMA and MACD rules, we contribute to the literature by using a panel data framework to examine the impact of macroeconomic factors and historical episodes on technical trading rules profitability in the GM and GA periods.

Our empirical results fill the gaps in the existing literature and suggest the following;

1. Based on the WBAVR and AQ tests, there is substantial evidence of cyclical swings between efficiency and inefficiency periods, most especially in emerging and frontier stock markets. The most efficient markets are in Japan, Canada and Brazil, whereas the least efficient markets are in Ukraine, Kenya and Nigeria. The 2008 stock market crash and 2014/2015 Eurozone debt crisis indicate that adverse market conditions do indeed cause high return predictability, hence violation of EMH. We also provide evidence that the degree of market efficiency vary over time and across markets, which shows consistency with the AMH framework. We allude to the change in volatility as a source of varying predictability differing between the GM and GA periods.
2. The predictive power of the AMA and MACD trading rules is stronger during the GM period than the GA period in most emerging and frontier markets, and less predictive power is evident in most developed markets. This suggests that there are opportunities for potential profits to be exploited due to time-varying market efficiency. The possibility that investment strategies deliver large or negligible profits over time conditional on market dynamics corroborates with AMH.
3. On a risk-adjusted basis by estimating Jensen's alphas, the AMA buy trading signals generate significant positive alphas for few emerging and many frontier markets in both GM and GA periods. Whereas, on the basis of dynamic technical trading rule profitability, the AMA rule has particularly beaten the MACD rule and buy-and-hold strategy in at least half of the understudy markets over time. This suggests that the use of technical trading rule is profitable, especially when the market is volatile and investors' reactions to learn and adapt to changing market conditions are slow. We conclude that the evidence of technical trading rule profitability in these markets may be caused by information frictions common to immature markets, which is consistent with the AMH paradigm.

4. On the basis of examining the drivers of trading rule profitability, we find that macroeconomic volatility (output and inflation) increases trading rule profitability more significantly in GM period and less significantly in GA period. Contrarily, changing market conditions such as Eurozone debt crisis, global financial crisis, 11th September 2001 terrorist attack and internet bubble bust have caused significant decline in trading rule profitability. This suggests that the influence of macroeconomic fundamentals and market conditions on trading rule profitability supports AMH framework.

The remainder of the chapter is structured as follows. Section 1.2 reviews the existing literature on EMH and AMH. Section 1.3 sets out the empirical methods of return predictability measures and technical trading rules. Section 1.4 describes the data and reports some preliminary statistics. Section 1.5 discusses the empirical results and their implications. Section 1.6 summarizes and concludes the chapter.

1.2 Literature Review

Efficient market has been defined in different ways by scholars but the definition given by Timmermann and Granger (2004, p. 21) incorporate the highest level of empirical information; "efficient market is a market in which predictability of asset returns, after adjusting for time-varying risk-premia and transactions costs, can still exist but only 'locally in time' in the sense that once predictable patterns are discovered by a wide group of investors, they will rapidly disappear through these investors' transactions." Apparently, this definition inculcates the attributes of market adaptability in the prediction of asset returns, though profit opportunities will quickly fizzle out when information becomes widely available and acted upon by market participants.

The proponents of the EMH have argued that markets learn very fast as new information arrives, thus, eliminating abnormal profit very quickly. On the contrary, pioneers of the AMH argue that agents continue to learn as new information arrives, thereby creating profit opportunities that can be exploited by investors from time to time. However, if it is assumed that rational agents have learning capabilities then any stable forecasting model could later become ineffective, which in turn makes it difficult to have uniquely outstanding forecasting procedures to generate unlimited profits. Therefore, it is important to note that the use of technical analysis does not automatically imply inefficiency since we know the underlying assumption of efficient markets is the power of competitive market forces to arbitrage excess returns away (see, Malkiel, 2003).

This chapter begins in section 1.2.1 with a brief historical development of EMH and the emergence of AMH. We discuss the empirical evidence on EMH and AMH in section 1.2.2. We finally present the existing empirical evidence on technical trading rules in section 1.2.3.

1.2.1 Historical Development of EMH and Emergence of AMH

The foundation of EMH was laid over a century ago, when Bachelier (1900) analysed the mathematical theory of random processes and argued that the stock price movements follow a Brownian motion (that is, random walk), hence, stock prices are unpredictable. After many years, Alexander (1961) finds that filter techniques generate profitability in stock market trading but later in 1964, he discovers that profitability disappears once trading costs are introduced. Furthermore, Granger and Morgenstern (1963) find that stock prices move in a short-term random walk but not in the long-run. In contrast, Samuelson (1965) produces a sequence of non-linear programming solutions to spatial pricing models with certainty and argues that price variation in informationally efficient markets cannot be predicted if market prices fully reflect the information disseminated from all market participants.

In order to give empirical backing to EMH, Fama (1963, 1965a, 1965b and 1970) measures the statistical properties of market prices. According to Fama (1965), efficient market is described as a market where there are large markets of rational profit maximisers actively competing with each other trying to predict future market prices of individual securities, and where important current information is almost freely available to all participants. Reviewing the empirical evidence in the 1960s, Fama (1970) describes three different types of market efficiency; first, *strong-form efficiency* – all public and private information is accounted for in stock price, thus making it even impossible for insider trader to make abnormal gains; second, *semi-strong efficiency* – all publicly available information is reflected in the current stock price, hence neither technical or fundamental analysis can be used to achieve abnormal gains; finally, *weak form efficiency* – all market information is fully incorporated in the stock price and therefore return is purely unpredictable from past prices.[5] Fama (1970, pg. 387) presents an interesting statement to describe the notion of informational efficiency;

> 'First, it is easy to determine *sufficient* conditions for capital market efficiency. For example, consider a market in which (i) there are no transaction costs in trading strategies, (ii) all available information is costless available to all market participants, and (iii) all agree on the implications of current information for the current price and distributions of future prices of each security'

However, he quickly admits that these conditions are practically unrealistic and remarked afterwards that though these conditions are sufficient for market efficiency, they are not necessarily sources of market inefficiency.

One of the key assumptions of EMH is the unbounded rationality of economic agents. However, Sargent (1993) adopts the notion of bounded rationality in contrast to perfect rationality in a manner to describe how traders with limited information about fundamental values develop expectation price models. Further development by Hommes (2001) demonstrates that financial markets can be modelled as adaptive belief systems dominated by bounded rational agents.

Subsequently, a new version of EMH called AMH was developed by Lo (2004). He argues that market prices incorporate information determined by a mixture of environmental elements and

[5] One common example to assess semi-strong form efficiency is based on firm-specific information event such as post-earnings announcements.

a number of market participants. According to Lo (2004), rationally bounded economic agents make decision to derive satisfactory outcome rather than optimal outcome obtained by rationally unbounded economic agents. This attribute of 'satisfactory outcome' cannot be attained analytically but rather through an evolutionary process of trial and error and natural selection (Lo, 2004). He further asserts that the violations of rationality inconsistent with market efficiency such as loss aversion, overreaction and other behavioural biases are consistent with an evolutionary paradigm of agents adapting to a changing market environment via a plain heuristic.

1.2.2 *Empirical Evidence on AMH and EMH*

The conventional approach for testing weak-form efficiency has been criticised for addressing absolute or perfect market efficiency. Rather, Campbell *et al.* (1997) suggest a notion of relative efficiency as a way of measuring the degree of market efficiency over time. Similarly, Lim and Brooks (2011) argue on the rationality to expect market efficiency to evolve over time due to varying underlying market elements such as characteristics of market microstructure, market imperfections and regulations, limits to arbitrage, psychological biases, noise trading and information technology. In addition, Griffin *et al.* (2010) posit that stock market efficiency may be increasing in the presence of better regulatory structure, higher economic/financial development, better information environment and lower trading costs. Given the changing market conditions prevalent in the financial markets, there is a growing empirical evidence supporting the time-varying efficiency nature of the EMH.

Focusing more on recent literature, Chang *et al.* (2004) examine return predictability in emerging markets using multivariate variance ratio. They find that emerging equity markets do not resemble a random walk, while a random walk was not rejected for developed countries (US and Japan). Worthington and Higgs (2005) investigate the weak form efficiency of 10 Asian emerging markets and 5 developed markets. Using various statistical tests, they suggest weak form efficiency in all markets but results for variance ratio tests are mixed.

In another case, Moreno and Olmeda (2007) analyse the predictability and profitability of 49 developed and emerging markets using artificial neural networks. They find that nonlinear models do not provide superior predictions than the linear models, and that developed and emerging stock markets are generally unpredictable when total transaction costs are accounted for.

Furthermore, Lim (2007) uses the portmanteau bi-correlation test through a rolling sample framework to investigate market efficiency of 11 emerging and 2 developed markets. The findings show that market efficiency evolves over time in a manner that is consistent with the AMH. Also, McPherson and Palardy (2007) investigate whether stock returns for 9 international markets are predictable using generalised spectral test. They find that most of the predictability to be non-linear in nature.

Similarly, Lim *et al*. (2008) examine the weak-form efficiency of 10 Asian emerging stock markets using a battery of nonlinearity tests. They find that returns series contain predictable nonlinearities after removing linear serial correlation from the data. Their findings demonstrate that the cross-country differences in market inefficiency can be explained by market size and trading activity but not market liquidity and the legal environment of the country.

Ito and Sugiyama (2009) examine the degree of time varying market efficiency of monthly S&P 500 returns using a time varying autocorrelation. Their results show consistency with AMH, with the US market most inefficient during the late 1980s and becoming efficient around 2000.

Griffin *et al*. (2010) compare the relative efficiency of 56 international stock markets using variance ratio statistic over the period of 1994 to 2005. The random walk tests suggest that individual stock and portfolio returns in emerging markets do not deviate more from a random walk than those in developed markets. They also find that due to higher transaction costs in emerging markets, trading strategies that exploit information in past returns are less profitable than in developed markets.

Kim *et al*. (2011) examine AMH by providing strong evidence of time-varying return predictability of the DJIA index from 1900 to 2009. They use automatic variance ratio test, automatic portmanteau test and generalised spectral test to obtain monthly measures of the degree of stock return predictability by applying a moving subsample window. They find that return predictability is driven by changing market conditions, consistent with the implication of the AMH. Using regression analysis, they find stock market volatility, economic fundamentals, political and economic crises are associated with return predictability.

Smith (2012) tests the martingale hypothesis for 15 European emerging and 3 developed stock markets using rolling window variance ratio. He finds that the degree of weak-form informational efficiency varied widely suggesting consistency with AMH. Similarly, Lim *et al.* (2013) examine the return predictability for US stock indices (S&P 500, DJIA and NYSE composite) using automatic portmanteau Box-Pierce test and wild bootstrapped automatic variance ratio test. They argue that markets oscillate around efficiency and inefficiency periods in a manner consistent with the AMH.

Rejeb and Boughrara (2013) assess the impact of financial liberalisation on the degree of informational efficiency in 13 emerging stock markets from 1986 to 2008, while considering three types of financial crises, which include banking, currency and twin crises. Using a treatment effects models with time-varying parameters, they find that there is a greater efficiency in recent years and that financial liberalisation not only improves the degree of efficiency but also reduces the probability of financial crises. Soufian *et al.* (2013) present three testable hypotheses to determine the degree to which observed trading behaviour conforms to the tenets of bounded rationality. They find that the AMH gives a theoretical basis for a new financial paradigm which better describes the financial crises.

Urquart and Hudson (2013) investigate the AMH using the long run historic data of US, UK and Japanese markets. By applying a linear autocorrelation, run and variance ratio tests, they provide evidence that the markets are adaptive, with returns going through periods of independence and dependence. For non-linear (McLeod Li, Engle LM and BDS tests), the markets show strong dependence for every subsample in each market. They conclude that the AMH provides a better description of the behaviour of stock returns than the EMH.

Zhou and Lee (2013) examine the time variation of the US Real Estate Investment Trust (REIT) market using a rolling window framework to estimate the automatic variance ratio and automatic portmanteau statistics. They find that the degree of REIT return predictability is time-varying and is influenced by market conditions such as the level of market development, inflation and overall equity market volatility.

Ghazani and Araghi (2014) evaluate the existence of the AMH as an evolutionary alternative to the EMH by applying daily returns on the TEPIX index from 1999 to 2013. Using the linear (automatic variance ratio and automatic portmanteau) and non-linear (generalised spectral and McLoed Li) tests, they find the vacillation nature of returns about dependency and independency which is consistent with the AMH.

Hull and McGroarty (2014) investigate 22 emerging markets using the Hurst-Mandelbrot-Wallis rescaled range as a measure between price efficiency and market development. They find evidence against weak form EMH and conclude the persistent market memory is consistent with AMH. Similarly, Mobarek and Fiorante (2014) apply a bias-free statistical technique to daily data of the equity markets in Brazil, Russia, India and China (BRIC) and detect the existence of weak-form efficiency.

Manahov and Hudson (2014) develop various artificial stock markets using a special adaptive form of the Strongly Typed Genetic Programming (SGTP) learning algorithm. Applying the technique to FTSE 100, S&P 500 and Russell 3000, they find stock market dynamics and nonlinearity are consistent with the evolutionary process of AMH because different trader populations behave as an efficient adaptive system involving over time. Also, Verheyden *et al*. (2014) apply multiple state-of-the-art rolling efficiency tests of S&P 500, EuroStoxx 50 and NIKKEI to confirm the validity of AMH. They find that the idea of dynamic and time-variant efficiency to be valid.

Very recently, Smith and Dyakova (2016) investigate the degree of return predictability in North and South American stock markets for the period from 1994 to 2011. Using a rolling window linear tests, they find the degree of return predictability varies widely and predictability largely coincides with period of crisis.

Based on the review of the foregoing literature, the empirical studies of EMH and AMH have largely focused on developed markets, much less on emerging and frontier markets. The results have been mixed although the developed markets portray higher market efficiency than the emerging markets. However, areas of dynamic return predictability using recent methodology for diverse markets have been under-researched. Since, market efficiency may exhibit distinct dynamics in periods of tranquillity and turbulence, it is therefore imperative to examine the degree of market efficiency when the state of economy changes. In this chapter, we consider linear tests of absolute and relative return predictability in developed, emerging and frontier stock markets.

1.2.3 *Empirical Evidence on Technical Trading Rules*

Technical trading is a method of searching the past prices of a time series for similar patterns that have the ability to predict future price movements with the aim of earning abnormal profit. According to Metghalchi *et al.* (2011), technical analysis is based on proposition that prices shift in trends, which are determined by the changing attitudes of traders towards different economic, political and psychological forces. This suggests that technical analysis is a method used for predicting trends of asset prices. In fact, Menkhoff (2010) argues that the substantial majority of fund managers use technical analysis and it is preferred to fundamental analysis. The use of technical analysis is a common practice among traders even though researchers have disputed on the reliability of using technical trading rules as a means of exploiting potential profit opportunities.

According to Neely *et al.* (2014), there are four types of theoretical models that explain why technical indicators can have predictive ability. Firstly, there are possibilities of investors receiving information at different times. As a result of *information frictions,* technical analysis can be used to assess whether information has been fully incorporated in asset prices (see Treynor and Ferguson, 1985; Brown and Jennings, 1989; Grundy and McNicholas, 1989; Blume *et al*., 1994). Secondly, there are different responses to information as a result of heterogeneous investors. Recent paper by Cespa and Vives (2012) evince that asset prices can deviate from their fundamental values provided that there is a positive level of asset residual payoff uncertainty and/or persistence in liquidity trading. Thirdly, the level of investors' underreaction and overreaction to information. Investors may underreact or overreact to news because of behavioural biases (see De Bondt and Thaler, 1985; Dissinaike 1997; Hong and Stein, 1999). Finally, the efficacy of technical analysis has been further elucidated with models of investor sentiment. Previous literature has shed light on how investor sentiment can cause asset prices to deviate from their fundamental values (see DeLong, 1990; Baker and Wugler 2006, 2007).

Furthermore, Park and Irwin (2007) explain reasons for technical trading profits based on theoretical models and empirical propositions. On the theoretical side, they highlight market frictions such as noise in current equilibrium prices, traders' sentiments, herding behaviour, market power or chaos. On the empirical side, Central Bank interventions, order flow, temporary market inefficiencies, risk premiums, market microstructure deficiencies or data snooping have been put forward as explanations for technical trading profits. Without doubt, there are many other factors that may drive technical trading profits.

The seminal paper by Brock *et al.* (1992) revived the study of return predictability and profitability using technical trading strategies. They test 26 technical trading rules under moving averages and trading range breaks on the daily price of Dow 30 spanning from 1897 to 1986. They find that buy signals steadily generate higher returns than sell signals, and therefore provide evidence for the predictive power of the technical rules. Replicating similar research methods on FT30 index from 1935 to 1994, Hudson *et al.* (1996) find that trading rules are reasonably successful in producing a return exceeding the buy-and-hold strategy. On the contrary, Bessembinder and Chan (1998) find that the inclusion of trading costs and adjustments for non-synchronous trading eliminate the profitability of technical trading in US data.

Furthermore, Ratner and Leal (1999) examine technical trading strategies (VMA and TRB rules) in the emerging equity markets of Latin America and Asia. They find that 82 out of 100 country-trading rule combinations correctly predict the direction of change in the return series when statistical significance is disregarded. However, only Taiwan, Thailand and Mexico emerge as markets where technical trading strategies may be profitable. Similarly, Ito (1999) investigates the trading rules on the national equity indices of six Pacific-Basin countries and finds that the rules have predictive power in Japan, Canada, Mexico and Taiwan, with the exception of US.

Tian *et al*. (2002) explore predictability and profitability of technical trading rules in the stock markets of US and China. They find that trading rules have no predictive ability after 1975 in US while technical trading rules have predictability and profitability for the Chinese markets across the 1990's (see also Cai *et al.* 2005).

Ellis and Parbery (2005) investigate the comparative performance of an adaptive moving average (AMA) on Australian All Ordinaries, DJIA and S&P 500 stock market indices. They find that the returns to the AMA could not offset the cost of trade, thereby lending support for the use of long run passive strategy.

Finfield *et al.* (2005) analyse if technical trading rules have predictive ability in eleven European developed and emerging stock market indices from 1991 to 2000. Unlike the developed markets, they find that emerging markets display some degree of return predictability suggesting that these markets are informationally inefficient. They also find that the small size filters consistently outperformed the buy-and-hold strategy in the emerging markets after accounting for transaction costs, while the performance of the MA rule was irregular and varied dramatically from market to market.

In Asian-Pacific equity markets, Lento (2006) studies the effectiveness of 9 technical trading rules in 8 countries and finds evidence of profitability in all countries except for Australia and Japanese stock markets. Similarly, Hoque *et al*. (2007) find that stock price behaviour in 8 emerging Asian markets exhibit inter-temporal predictability, suggesting that future returns may be forecasted by astute investors.

Chen *et al.* (2009) investigate various technical trading rules from 1975 to 2006 in 8 Asian markets and find that the short term MA rules are most profitable for all markets when no transactions cost are considered but when they are considered, the most profitable rules are the long-run MA rules.

Schulmeister (2009) examines how technical trading exploits the momentum effect and reversal effect in the S&P 500 spot and futures markets using daily and intraday data. Based on daily data, the profitability of 2580 technical models has steadily declined since 1960 and yielded no profits since the early 1990s. Based on 30-minutes data, an average of 7.2% per year gross return is generated between 1983 and 2007. He concludes that the results could be an indication that stock markets are becoming efficient or the stock price trends shifting from 30-minutes-prices to prices of higher frequencies.

Metghalchi *et al.* (2012) investigate the profitability of the MA rule in 16 European stock markets from 1990 to 2006. They find predictive power in all of the countries and the technical trading rules outperform the buy-and-hold strategy. In contrast, Shynkevich (2012) finds that after adjusting for data snooping bias, technical trading rules cannot outperform buy-and-hold strategies.

Ülkü and Fang (2013) investigate the determinants of technical trading rule profitability (MA and MACD) from 2001 to 2012. They find that MACD rule's profitability is insignificant and lower than that of MA rules. They also show that the interaction of the return volatility with the return persistence and macroeconomic volatility have significant positive effect on technical rule profitability. They conclude that the presence of an index futures market significantly causes a decline in profitability of both technical rules.

Yu *et al.* (2013) investigate whether the VMA, FMA and TRB rules can predict stock price movements and outperform a simple buy-and-hold strategy after adjusting for transactions costs in Southeast Asia over the periods from 1991 to 2008. They find that the trading rules have stronger predictive power in the emerging markets of Malaysia, Thailand, Indonesia and the Philippines than in the more developed stock market of Singapore. However, by accounting for transaction costs, the trading profits were eliminated suggesting that the market is weak-form efficiency.

Fang *et al.* (2014) examine predictability of the simple technical trading rules (VMA, FMA and TRB) using an out-of-sample test for DJIA and S&P500 composite price index. Their test safeguard against selection bias, data mining, hindsight bias and other biases that may affect results. They find no evidence that technical trading rules have statistically significant predictability out-of-sample.

Taylor (2014) examines the performance of momentum-based technical trading rules (TTRs) applied to all constituents of the DJIA stock index from 1928 – 2012. He finds that profits evolve slowly over time and success in TTRs depends on financial markets conditions, primarily (non)liquidity, and to a lesser extent macroeconomic (in)stability, including the ability to short-sell stocks.

Stankovic *et al.* (2015) examine the efficacy of technical analysis and predictive modelling of stock indices of emerging markets. They find that trading strategies based on Least Squares

Support Vector Machine (LS-SVMs) model outperformed all technical trading strategies (EMA and MACD) and the buy-and-hold strategy.

Apart from the stock market, technical analysis is widely used in other markets, particularly foreign exchange market of developed and emerging market countries (for recent survey studies, see Taylor and Allen, 1992; Cheung and Wong, 2000; Lee *et al*. 2001; Olson, 2004; Menkhoff and Taylor, 2007; Gradojevic, 2007; Tabak and Lima, 2009; Owen and Palmer, 2012).

In summary, the application of technical trading strategies presents mixed results. It appears that many findings indicate that predictive power of technical analysis is greater in small and medium sized capitalised markets (e.g. emerging markets countries) than in developed markets. To our knowledge, the comparisons between AMA and MACD rules have not been investigated, particularly for diverse markets in periods of stability and crisis. Similarly, there is scant empirical evidence on testing the profitability of investment trading strategies in frontier markets. Likewise, few empirical studies have examined the determinants of trading rule profitability which is critical for portfolio analysis (see Lagoarde-Segot and Lucey, 2008; Lim *et al*., 2008; Cialenco and Protopapadakis, 2011; Owen and Palmer, 2012; Ülkü and Prodan, 2013; Taylor, 2014). Apart from macro-finance determinants, the inclusion of historical episodes will further shed light on technical trading rule profitability. In this chapter, we shall discuss the empirical results of testing the short-horizon trend-following rules and the determinants of technical trading rule profitability, thus linking the empirical findings to AMH framework.

1.3 Methodology

A market is efficient/inefficient if stock returns are independent/dependent with no predictability/unpredictability throughout the sample. In contrast, a market is adaptive if there are fluctuations between independence/unpredictability and dependence/predictability of returns over the time period. The degree of market efficiency is measured using Wild Bootstrap Automatic Variance Ratio (WBAVR) and Automatic Portmanteau (AQ) tests. The statistical measures of return predictability are constructed under the null of random walk hypothesis, also implying weak-form efficiency. In other words, the WBVAR and AQ statistics test the null hypothesis of return unpredictability in the conditional mean of the markets under scrutiny.

If return predictability is established, then technical trading strategies can be used to exploit potential profits under the assumption of no trading costs. Therefore, we employ adaptive moving average (AMA) and moving average convergence divergence (MACD) rules because both are non-linear trend-following mechanism and will be able to discover trend fluctuations at an early phase. Also, both trading rules can minimize whipsaw signals generated by false trading.

The measures of return predictability or dependency consider linear tests using WBAVR and AQ tests. Recent studies that have used these tests of return predictability though with a limited dataset include, Lim *et al.*, 2011; Kim *et al.* 2011; Urquhart and Hudson, 2013.

1.3.1 *Wild Bootstrap Automatic Variance Ratio Test*

The variance ratio (VR) test has been an established method to examine the weak form market efficiency, dating back to the work of Lo and MacKinlay in 1988. The test account for conditional heteroscedasticity and is based on the statistical proposition that under the null hypothesis of serially uncorrelated returns, the variance of the *k*-period return is equal to *k* times the variance of the one-period return. The VR test statistics is expressed as;

$$VR(k) = \frac{Var(r_t(k))}{kVar(r_t)} = 1 + 2\sum_{j=1}^{k-1}(1 - \frac{j}{k})\rho_j \tag{1.1}$$

where $r_t \equiv r_t + r_{t-1} + \ldots + r_{t-k+1}$ and ρ(j) being the j^{th} order autocorrelation of r_t.

The VR test is considered to have more optimal power than other alternatives (See Lo and MacKinlay, 1989; Richardson and Smith, 1991; Faust, 1992). To improve on the VR method, Choi (1999) evaluates the vector of holding periods of *k* based on the data-dependent method of Andrews (1991) for spectral density at the zero frequency. The test statistics, named automatic variance ratio (AVR) is written as;

$$\text{AVR}(\hat{k}) = \sqrt{\frac{T}{\hat{k}}}\,\frac{[VR(\hat{k})-1)}{\sqrt{2}} \xrightarrow{d} N(0,1) \qquad (1.2)$$

where, VR$(\hat{k})$ = $1 + 2\sum_{j=1}^{T-1} m(\frac{i}{\hat{k}})\hat{\rho}_i$ and $m(x) = \frac{25}{12\pi^2 x^2}\left[\frac{\sin(6\pi x/5}{6\pi x/5} - \cos(\frac{6\pi x}{5})\right]$ is a weighing function with positive but diminishing weights. Simply put, the AVR is a weighted sum of autocorrelations with positive and decreasing weights. The statistic is asymptotically standard normal under the assumption of identically and independently distributed returns. To deal with the problem of size distortion in small samples when there is conditional heteroscedasticity in returns, we use the three steps of wild bootstrap procedure proposed by Kim (2009).

Step 1: A bootstrap sample of *n* observations is formed as $Y_t^* = \eta_t Y_t$ (t = 1,…,n) where η_t is a random sequence with E(η_t) = 0 and E(η_t^2) = 1 in order that any non-normality and heteroscedasticity in the original return series are preserved in Y_t^*.

Step 2: Compute $AVR^*(k^*)$ based on the AVR statistic obtained from $\{Y_t^*\}_{t=1}^{T}$.

Step 3: Replicate steps 1 and 2 *B* times to form a bootstrap distribution $\left\{AVR^*(\hat{k}^*; j)\right\}_{t=1}^{B}$

The two-tail *p*-value of the test can be obtained by computing the proportion of the absolute values of the bootstrap distribution $\left\{AVR^*(\hat{k}^*; j)\right\}_{t=1}^{B}$ that are greater than the absolute value of the observed statistic AVR$(\hat{k})$ for real data. The AVR statistical values indicate positive (negative) autocorrelation in stock returns but the absolute values are commonly used because less autocorrelations are exhibited in both directions for a more efficient market.

According to Tabak *et al*. (2009), the bootstrap involves normalising returns by multiplying each observation of actual returns by a corresponding random factor and resampling from these normalized returns. The WBAVR is constructed to reproduce the conditional and unconditional heteroscedasticities existing in the data and it greatly improves the small sample properties of the AVR test. This suggests that it provides statistical inference robust to heteroscedasticity (see Kim, 2006). We use 500 bootstrap iterations to perform the AVR test given the report by Charles *et al.* (2011) that it has no size distortions and possesses excellent power against wide range of linear and non-linear models.

1.3.2 *Automatic Portmanteau Test*

The Portmanteau test was first proposed by Box and Pierce (1970) as a tool to test if the first *K* autocorrelations of a financial time series are zero (i.e. an indication of unpredictability).

Let Y_t be a financial return at time *t*, where $i = 1, 2, \ldots, T$. The sample mean is represented as $\bar{Y}$. Then, the AQ test statistics is defined as;

$$\text{AQ} = Q_K = T\sum_{j=1}^{K}\hat{\rho}_j^2 \tag{1.3}$$

where $\hat{\rho}_j = \frac{\hat{\gamma}_j}{\hat{\gamma}_0}$ is the *jth*-order sample autocorrelation, and $\hat{\gamma}_j = \frac{1}{T-j}\sum_{i=1+j}^{T}(Y_t - \bar{Y})\,(Y_{t-j} - \bar{Y})$, $j = 0, \ldots, T-1$.

Lobato (2001) later modified the test statistic to accommodate the conditional heteroscedasticity prevalent in financial returns. The modified test statistics is given as;

$$Q_K^* = T\sum_{j=1}^{K}\tilde{\rho}_j^2 \tag{1.4}$$

where $\hat{\rho}_j^2 = \frac{\hat{\gamma}_j^2}{\hat{\tau}_j^2}$, and $\hat{\tau}_j^2 = \frac{1}{T-j}\sum_{i=1+j}^{T}(Y_t - \bar{Y})^2\left(Y_{t-j} - \bar{Y}\right)^2$,

where $\hat{\gamma}_j$ is the estimator for the autocovariance of Y_t and $\hat{\tau}_j^2$ the autocovariance of Y_t^2.

For automatic determination of the value of K from the data, Escanciano and Lobato (2009a) propose to choose K based on the combination of Akaike Information Criteria (AIC) and the Bayesian Information Criterion (BIC). The AQ test based on the optimal value of $\widetilde{K}$ is written as follows;

$$Q_{\widetilde{K}}^* = T\sum_{j=1}^{\widetilde{K}}\tilde{\rho}_j^2 \tag{1.5}$$

where the optimal $\widetilde{K} = min\{K : 1 \leq K \leq d;\ L_K \geq L_h,\ h = 1,2,\ldots,d\}$, *where* $L_K = Q_{\widetilde{K}}^* - \pi(k, T, q)$, d is a fixed upper bound and π a penalty term. As a result of extensive simulation studies, Escanciano and Lobato (2009a) suggest that $q = 2.4$ achieves the best combination of the two information criteria. On a final note, the AQ statistic asymptotically follows the chi-squared distribution with one degree of freedom under the null hypothesis of no return predictability (see Kim *et al.,* 2011; Lim *et al.,* 2011; Zhou and Lee; 2013).

Contrasting both tests, the AQ statistics overcome the complications of the AVR statistics of generating autocorrelations of different signs because it is based on the sum of the squared return autocorrelations (Escanciano and Lobato, 2009b). Similarly, the AQ test is an asymptotic test, while the AVR test is small sample test based on wild bootstrapping robust to heteroskedasticity. According to Charles *et al.* (2011), the AVR test possesses higher power (i.e. higher probability of rejection under null hypothesis) with no size distortion (i.e. the difference between the actual size (actual significance level) and the nominal size (nominal significance level e.g. 5%) when compared with the AQ test.

Turning to technical trading analysis, it is a way of systematically exploiting profits from frequent occurrence of asset price trends. According to efficient market theorists, technical analysis will not be able to generate excess returns in an efficient market. The weak form efficiency of the stock market is violated if identifying patterns in past stock market prices can predict market returns. In contrast, technical traders believe that market inefficiencies exist in some forms which therefore makes it possible to forecast future prices movement using past prices or volumes and beat the simple buy-hold strategy.

We therefore narrow our analysis to two contrasting short-horizon technical trading rules, namely the AMA and MACD rules. The selected trading rules are compared with the buy-and-hold strategies under different economic conditions that is, the periods of 'Great Moderation' and 'Great Austerity'. The comparative analysis of the trading rules enables us to quantify the levels of profitability in periods of tranquillity and turmoil.

1.3.3 *Adaptive Moving Average (AMA) Rule*

The simple moving average (SMA) is a measure of the average value of a security's price over a period of time and thereby creates a trend by smoothing irregular price movements. In other words, the SMA is a simple parametric equally weighted linear measure of the average values of a specified number of previous closing prices, hence, it minimizes the effects of outliers that appear in extreme reactions to news. Undoubtedly, SMA can remove known seasonal or cyclical effect and gives smoother trends when averaging longer periods.

The SMA is given by;

$$SMA_t = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-1} \tag{1.6}$$

where P_t is the stock price at time *t*; the number of periods is denoted as *n.*

As a result of the fixed length of the underlying moving average, the SMA system is deficient in ranging markets characterised by no clear trend in movement. This shortcoming is surmounted by the adaptive moving average (AMA) proposed by Kaufman in 1995.

In order to avoid false signals due to noise, the AMA is premised on the fact that short-term (fast) MA will react more rapidly when market prices are trending (that is, erratic and unpredictable), but a long-term (slow) MA will be preferred when markets are ranging (that is, stable). According to Ellis and Parbery (2005), the AMA system has the capacity to react automatically to changing market conditions by effectively changing the length of the underlying MA dependent upon the level of volatility in the market.

The AMA rule uses the mechanism referred to as efficiency ratio (ER) to identify and adapt to changing market conditions. The ER is also called generalised fractal efficiency, derived from the concept of fractal efficiency (Peter, 1994) and applies a technique that reproduces the classical rescaled range of Hurst (1951). The efficiency ratio is used to measure the market speed and swing, and ranges from 0 when markets are very noisy and market movements are directionless, to +1 when markets movements are deemed more efficient, less noisy and highly directional.

Against this backdrop, the first step to constructing an AMA system is to estimate the ER, calculated by dividing net price movement (price direction) by total price movement (volatility)

$$ER_t = \frac{D_t}{V_t} \tag{1.7}$$

where price direction, D_t is the *n*-day change in price

$$D_t = P_t - P_{t-n} \tag{1.8}$$

$$V_t = \sum_{i=1}^{n} |P_t - P_{t-i}| \tag{1.9}$$

where volatility, V_t is the sum of the absolute value of daily price changes.

If the overall price change relative to high volatility is low then the value of ER will be closer to 0, whereas if the overall change in price relative to low volatility is high then the ER will be nearer to 1. In selecting the number of days for estimation, Kaufman (1995, p.146) uses 10 days based on the premise that a lower number of days will generate unstable ER while a higher number of days will generate a more stable noisy relationship.

The second step is to use an exponentially weighted moving average of the form;

$$AMA_t = AMA_{t-1} + SC_t(P_t - AMA_{t-1}) \tag{1.10}$$

where AMA_t is the current value of the AMA; AMA_{t-1} is the value of AMA in previous period, SC_t is the scaled smoothing constant at time *t* which is further expressed as;

$$SC_t = [SC_t(fastest - slowest) + slowest]^2 \tag{1.11}$$

The values of the fastest and slowest trends are given by Kaufman (1995) as an exponential smoothing constants of 0.6667 and 0.0645, respectively. The formulas used to derive these values are given as;

$$\text{Fastest} = \frac{2}{n_f+1} \tag{1.12}$$

$$\text{Slowest} = \frac{2}{n_s+1} \tag{1.13}$$

where the number of days in the fastest (n_f) and slowest (n_s) are set at 2 and 30, respectively. The faster trend is when the market is moving rapidly in one direction and it is prone to short-term volatility, frequent price shocks and intense competition in active stock trading. Whereas, the slower trend is when the price is slow to adjust in a ranging market.

The last step is to consider the use of filter in a trending system in order to avoid false signals caused by noise in a ranging market conditions.[6] The filter is calculated as a small percentage in the AMA trendline;

$z_t = AMA_t - AMA_{t-1}$

$Filter = y\sigma(AMA_t)$

$$\sigma(AMA_t) = \sqrt{\sum_{t=1}^{n} z_t^2 - \frac{(\sum_{t-1}^{n} z_t)^2}{n}} \quad (1.14)$$

where y is the percentage of standard deviation and Kaufman (1995) recommends y to be set at 0.15. The filter is calculated over a period of 10 days. To get a buy or sell signal, the one-period change in the AMA trendline must be bigger or smaller than the filter size. This is effective for selecting trades and eliminating false signals.

Based on the foregoing steps, the trading rules are generated as follows;

Buy when the AMA rises above a preceding n-period low by a number greater than the filter.

Sell when the AMA falls below a preceding n-period high by a number greater than the filter.

1.3.4 *Moving Average Convergence-Divergence (MACD) Rule*

The MACD rule represents the difference between short- and long-term exponential moving averages (EMA). The signals generated from the computation of an EMA of the MACD line is referred to as *trigger line*. EMA is specified as;

$$EMA(n)_t = \frac{2}{n+1}(P_t - EMA_{t-1}) + EMA_{t-1} \quad (1.15)$$

where P_t is the closing price of the stock index on day t, and n is the number of periods for estimating EMA. The preliminary EMA is the n-day simple MA of the series. The MACD rules are identified by (short(s), long(l) and signal(g)). The MACD is therefore calculated as;

$$MACD(n)_t = EMA(s)_t - EMA(l)_t \quad (1.16)$$

[6] By incorporating filters, weak trading signals are eliminated.

where *s (short)* indicates the lag length of short-term EMA, *l* (long) is the lag length of long-term EMA.

In order to generate the buy and sell orders of MACD rule, we use signals, represented as the lag length of the trigger line. This is expressed using a lag length of 9-days EMA of MACD line;

$$Signal(n)_t = EMA_9(MACD(n)_t) \tag{1.17}$$

This summarises the most commonly used MACD parameters among practitioners as MACD (12, 26, 9). Where '12' stands for short trading signal, '26' stands for long trading signal and '9' stands for the signal line. The position of the MACD line relative to the trigger line will generate the buy and sell signals. A long (short) trading signal is generated when the MACD line penetrates above (below) an upper (lower) band of the signal line. Invariably, a buy (sell) signal is generated when the MACD line crosses the trigger line up from below (down from above).

In this study, we follow Rosillo *et al.'s* (2013) method of generating buy and sell orders of MACD: a buy order is generated when *MACD(n)* is less than *0* and the *signal(n)* is less than *0*, and *Signal(n)* is greater than the *MACD(n);* a sell order is generated when the *MACD(n)* is greater than *0* and the *Signal(n)* is greater than *0*, and *signal(n)* is less than *MACD(n)*.

Analysing the aggregate daily returns that follow a signal is critical after testing the effectiveness of the trading rule sign prediction ability. It is expected that a large and positive daily return will follow a buy signal while a small or negative return will follow a sell signal. We perform the *t*-tests to investigate the differences between the mean buy/sell returns and the unconditional buy-and-hold returns.

$$t\text{-statistics for buys (sells)} = \frac{\mu_\tau - \mu}{\sqrt{\frac{\sigma^2}{n} + \frac{\sigma^2}{n_\tau}}} \tag{1.18}$$

where μ_τ and μ are the mean return for the buys or sells and the unconditional mean for the buy-hold strategy, respectively. Whereas, the n and n_τ are the number of observations for the buys or sells and buy-hold strategy. σ^2 is the estimated variance for the whole sample.

The null hypothesis to be tested is given as;

H_0: returns conditional on technical trading signals are not statistically different from the unconditional returns

The t-statistics for testing a significant difference between returns following the buy-sell (BS) signals is given as;

t-statistics for Buy-Sell = $\frac{\mu_b - \mu_S}{\sqrt{\frac{\sigma_b^2}{n_b} + \frac{\sigma_S^2}{n_S}}}$ (1.19)

where μ_b and μ_s are the mean return for the buys and sells whereas n_b and n_s are the number of signals for the buys and sells.

The null hypothesis that technical trading rules do not generate useful trading signals is given as;

H_0: buy signals should not be statistically different from sell signals in terms of returns conditional on these trading signals.

The standard t-tests assume normal, stationary and time-independent distributions (see Brocks *et al*., 1992), and as a result may be biased in evaluating the statistical significance of technical trading rule profits (see Ülkü and Prodan, 2013). We therefore utilise t-statistics obtained from the estimation-based bootstrap technique following the works of Brocks *et al.* (1992), Besseminder and Chan (1996), Ratner and Leal, (1999), Ülkü and Prodan (2013). The bootstrap methodology is inspired by Efron (1979), Friedman and Peters (1984) and Efron and Tibshirani (1986).

In summary, comparing the technical trading strategies of AMA rule with the MACD rule will be critically useful for short-horizon traders. In the empirical session, we will test whether the returns of the trading rules are greater than a buy-and-hold strategy and whether the mean buy is statistically different from the mean sell.

1.3.5 *Panel Regression Analysis*

The use of panel regression analysis will systematically examine the changing market conditions and economic fundamentals driving the cross-sectional and time variation of technical trading rule profitability. The panel regression model is estimated with both the fixed and random effect estimators. However, the Hausman test is used to check the appropriate method of estimation. We identify key macroeconomic variables and episodes that may potentially drive profitability; [7]

[7] We estimate the conditional volatilities with the GARCH (*1,1*) models.

The panel regression equation is therefore given as;

$$r_{it} = \beta_0 + \beta_1 vol_{stock_{it}} + \beta_2 vol_{output_{it}} + \beta_3 vol_{forex_{it}} + \beta_4 vol_{interest_{it}} + \beta_5 vol_{inflation_{it}} + \beta_6 vol_{volume_{it}} + \beta_7 vol_{futures_{it}} + \beta_8 dummy_{dot-com_{it}} + \beta_9 dummy_{housing-bubble_{it}} + \beta_{10} dummy_{GFC_{it}} + \beta_{11} dummy_{Eurozone-crisis_{it}} + \beta_{12} dummy_{sept11_{it}} + \varepsilon_{it}$$ *(Cross-sectional unit is i = 1,…., N; time period is t = 1,…, T).* (1.20)

where r_{it} is the monthly returns of AMA and MACD rules; $vol_{stock_{it}}$ is the conditional volatility of monthly stock returns; $vol_{output_{it}}$ is the conditional volatility of monthly industrial output growth rate; $vol_{forex_{it}}$ is the conditional volatility of monthly foreign exchange rates; $vol_{interest_{it}}$ is the conditional volatility of monthly 3-month interest rate; $vol_{inflation_{it}}$ is the conditional volatility of changes in monthly consumer price index (inflation rate); $vol_{volume_{it}}$ is the conditional volatility of monthly stock volume; $vol_{futures_{it}}$ is the conditional volatility of changes in monthly index futures market; $dummy_{dot-com_{it}}$ is the dummy variable for internet bubble bust (March 2000 – September 2002); $dummy_{housing-bubble_{it}}$ is the dummy variable for housing bubble (January 2005 – February 2007); $dummy_{GFC_{it}}$ is the dummy variable for global financial crisis (March 2007 – June 2009); $dummy_{Eurozone-crisis_{it}}$ is the dummy variable for Eurozone debt crisis (May 2010 – June 2015); $dummy_{sept11_{it}}$ is the dummy variable for September 11 attack and Afghanistan invasion (September 2001 – October 2001).

Having an understanding of the drivers of technical trading rule profitability is crucial for market practitioners. We discuss below the reasons for the inclusion of these explanatory variables and the theoretical implications underpinning the expected results. To start with, the dependent variables represented by the technical trading rule (TTR) returns are used because they are designed to beat the buy-and-hold returns irrespective of the performance of the underlying markets. Neely *et al.* (2009) and Ülkü and Prodan (2013) provide similar reason for using TTR returns as the dependable variable.

For the explanatory variables, the use of the conditional second moment may be adduced to the perception that higher risk slows down the incorporation of new information thereby creating opportunities for trading rule profitability. This perception was echoed by Hong and Stein's (1999) model that the intensity of fundamental news arrivals should increase TTR profitability. This suggests that the higher the volatility of fundamental news arrival, the better perhaps will be the performance of technical trading rules in exploiting asset prices deviating from their fundamental values.

For financial variables, we use the GARCH conditional variance of the stock returns as a proxy for market volatility. Kidd and Brorsen (2004) find that decline of technical rule profitability over time is associated with decrease in price volatility. Similarly, Ülkü and Prodan (2013) demonstrate that returns to technical rules increase with market volatility. We further consider stock volume conditional volatility as a measure of market depth. We expect that higher market depth, will reduce TTR profitability. The conditional volatility of index futures is used as a proxy for index futures market. Since we did not account for transaction costs, we consider that the presence of the index futures market is capable of reducing transaction cost, hence increasing market efficiency.[8] Ülkü and Prodan (2013) show that the presence of an active index futures market significantly reduces the profitability of the short-horizon technical trend-following rules after controlling for other indicators of market development.

For economic variables, we similarly use the GARCH model to obtain the conditional volatility of consumer price inflation, output growth, interest rate and exchange rate, as potential drivers of TTR profitability. According to Hong and Stein's (1999) model, important news arrival can generate volatility. This suggests that massive changes in economic fundamentals giving rise to trends can trigger high volatilities. We conjecture therefore that arrival of fundamental news can give rise to volatility, which in turn may cause TTR profitability to increase. Empirical evidence by Palmer and Owen (2012) find that exchange rate volatility has a significant positive effect on TTR profitability. In a similar fashion, Ülkü and Prodan (2013) find that macroeconomic volatility adds to technical rule profitability. The period of unexpected changes, shocks and crises should increase both economic and financial volatility, hence skilled investors could use technical rules to exploit profit opportunities created by asset price misalignments.

In summary, substantial literature has found the significant diminution of TTR profitability over time (see Olson, 2004; Schulmeister, 2009; Owen and Palmer, 2012). If the impact of macroeconomic fundamental, financial factors and market anomalies is associated with trading rule profitability, then this will provide further justification for AMH. The detailed empirical results will be discussed in subsequent sessions of this chapter.

[8] The index futures markets increase market liquidity and rapid incorporation of new information in asset prices due to the rising activities of short-horizon traders, thus leading to dramatic reduction in transactions costs (see Ülkü and Prodan, 2013).

1.4 Dataset

In this analysis, we use daily dataset that covers the period from 5th March 1999 to 5th March 2015 with a total observation of 4170 for each equity market.[9] Our sample consist of 11 developed, 10 emerging and 9 frontier equity markets and they exhibit distinctions in terms of depth, size and composition. In line with existing literature, the returns are based on domestic currency denominated indices (see for example, Jordan *et al.*, 2015; Vivian, 2016).

We report the preliminary statistics for each developed, emerging and frontier markets in Table 1.1. The closing stock prices are non-stationary but have been transformed into stationary series by computing their logged first differences and using ADF test to confirm that the returns series have no unit root. The highest and lowest daily stock returns of 0.084% and -0.012% are found in Pakistan and Italy, respectively. Among the specialised markets, MSCI emerging markets have the highest return of 0.028%. The MSCI frontier markets have the lowest standard deviation of 0.8%, followed by the MSCI developed markets while MSCI emerging markets and Euro Area markets (Euro Stoxx) have the highest standard deviation. Among individual markets, the highest and lowest standard deviation of 2.3% and 0.8% are found in Russia and Jamaica, respectively. In a similar vein, Figure 1.1 shows the graphical representation of the risk-return profile of the market indices under investigation. Apart from Ukrainian, Romanian and Argentine markets, the risk-return profile of individual frontier markets is far better than most emerging and developed markets. The worst performing markets in terms of risk level are in Turkey and Russia, whereas the worst performing market in terms of return level is in Italy.

The reward-to-volatility (i.e. Sharpe ratio) measures the risk-adjusted return for each market. Using UK market Sharpe ratio of -0.008 as a benchmark, 21 out of 30 portfolios outperformed the UK market on a risk adjusted basis. The negative Sharpe ratio in 11 out of 30 markets indicate that the investment return is lower than the risk-free rate. The Canadian market has the best Sharpe ratio while the Italian market has the worst Sharpe ratio among the developed markets. In the emerging markets, the Sharpe ratio of the Turkish market is the highest while the Brazilian market has the lowest. Overall, the Pakistan market has the highest Sharpe ratio while the Kenyan market has the lowest Sharpe ratio.

[9] The nine developed markets include FTSE 100 – UK; DAX 30 – Germany; CAC 40 – France; FTSE MIB 40 – Italy; S&P 500 – US; S&P/TSX – Canada; NIKKEI 225 – Japan; HANG SENG – Hong Kong; S&P/ASX 200 – Australia. The nine emerging markets include RTS – Russia; WIG – Poland; IPC – Mexico; BVSP – Brazil; CNX Nifty 50 – India; SSE composite index – China; BIST 100 – Turkey; EGX 30 – Egypt; FTSE/JSE – South Africa. The eight frontier markets include BET – Romania; PFTS – Ukraine; MERVAL – Argentina; JMI – Jamaica; NSE All share index– Nigeria; NSE 20 – Kenya; KSE 100 – Pakistan; CSE – Sri Lanka. The four specialised markets include MSCI World Index – Developed markets; MSCI Emerging Markets Index – Emerging markets; MSCI Frontier Markets – Frontier markets; Euro Stoxx 50 – Euro Area Market.

Furthermore, many countries exhibit negative skewness suggesting the prevalence of negative shocks than positive shocks. According to Post, Van Vliet and Levy (2008), the skewness of the distributions of financial asset returns are generally caused by information asymmetry and investors' preference. The high kurtosis values for all the series indicate fat-tailed distribution, presence of extreme observations and volatility clustering.

In summary, the risk-return benefits associated with the emerging and frontier markets could potentially yield higher gain for investors that diversify into these markets because they have better Sharpe ratio. In the next session, we explain how market efficiency changes over time and the application of technical trading strategies in generating profitability.

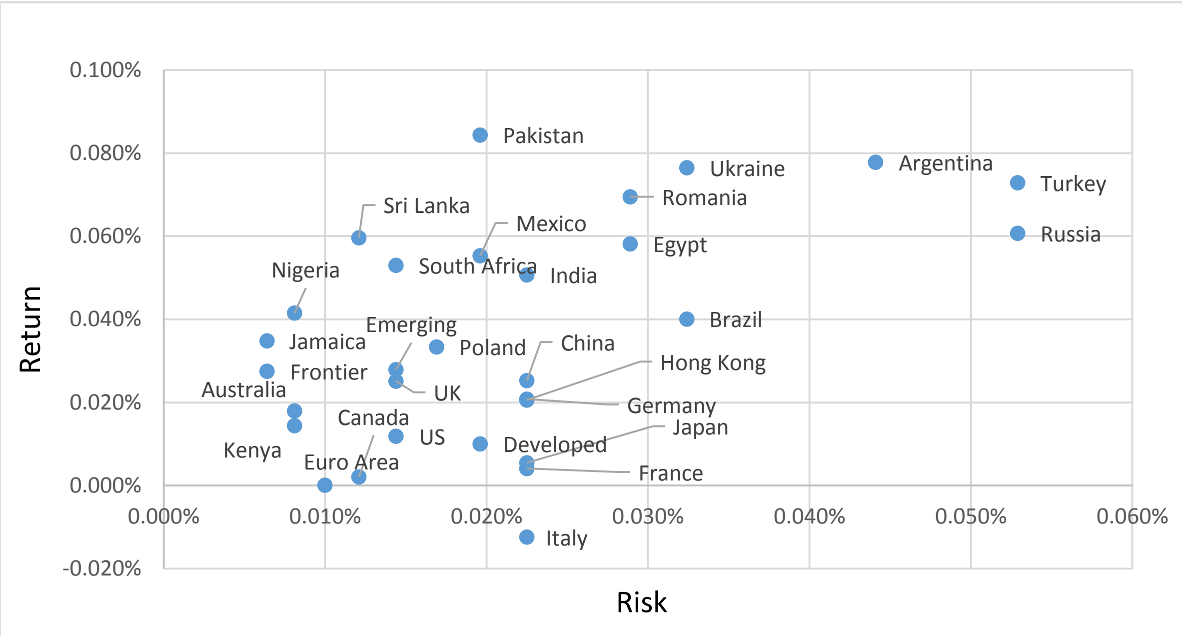


Figure 1.1: Mean-Variance of Stock Market Indices

Table 1.1: Descriptive Statistics

	Mean (*10^{-3})	**S.D.**	**Skw**	**Kur**	**Sharpe ratio**	**Q (12)**	**Q^2 (12)**	**ADF**
Panel A: Developed Markets								
UK	0.251	0.012	-0.160**	9.366***	-0.007	81.67***	3372***	-31.32***
Germany	0.208	0.015	-0.019	7.548***	0.008	22.06**	2699***	-30.26***
France	0.041	0.015	0.006	7.963***	-0.002	52.79***	2457***	-31.78***
Italy	-0.124	0.015	-0.082***	7.565***	-0.014	48.16***	2169***	-30.25***
US	0.119	0.012	-0.182***	11.25***	0.004	54.05***	4115***	-31.17***
Canada	0.021	0.011	-0.672***	12.53***	0.010	56.43***	4161***	-30.89***
Japan	0.055	0.015	-0.419***	9.674***	0.003	15.07	3538***	-29.28***
Hong Kong	0.206	0.015	-0.050	11.14***	-0.006	15.23	2870***	-29.77***
Australia	0.180	0.009	-0.487***	9.229***	-0.000	14.16	3267***	-29.59***
Developed	0.100	0.014	-11.78***	10.69***	0.000	97.44***	4602***	-29.85***
Euro Area	0.001	0.010	-0.334	7.513***	-0.005	1.546	2526***	-31.42***
Panel B: Emerging Markets								
Russia	0.607*	0.023	-0.333***	11.62***	0.010	64.51***	1589***	-28.33***
Poland	0.334*	0.013	-0.329***	6.354***	0.006	24.63***	1116***	-27.11***
Mexico	0.553**	0.014	0.074**	7.609***	0.019	57.35***	1671***	-30.21***
Brazil	0.401	0.018	-0.071*	7.020***	-0.007	13.00	2708***	-30.22***
India	0.507**	0.015	-0.229***	11.10***	0.016	55.19***	812.9***	-28.70***
China	0.253	0.015	-0.085**	7.802***	0.009	33.54***	639.1***	-27.63***
Turkey	0.729**	0.023	0.062*	9.873***	0.024	24.97**	1185***	-28.54***
Egypt	0.582**	0.017	-0.391***	12.38***	0.013	142.0***	548.4***	-27.38***
South Africa	0.530**	0.012	-0.176***	6.886***	0.019	45.58***	2601***	-30.48***
Emerging	0.279	0.012	-0.502***	11.06***	-0.002	6.195	4713***	-27.73***
Panel C: Frontier Markets								
Argentina	0.778**	0.021	-0.172***	7.894***	0.017	42.13***	999.5***	-29.24***
Jamaica	0.348**	0.008	0.611***	16.72***	-0.017	64.34***	178.8***	-23.61***
Romania	0.695**	0.017	-0.233***	18.64***	0.006	50.30***	1158***	-28.92***
Ukraine	0.765**	0.018	0.127***	15.35***	0.002	114.6 ***	456.9***	-25.76***
Kenya	0.144	0.009	0.302***	36.04***	-0.018	466.5***	1583***	-25.81***
Nigeria	0.415**	0.009	-0.088***	7.242***	0.000	976.5***	1794***	-26.20***
Pakistan	0.844***	0.014	-0.279***	6.909***	0.037	6.720	1885***	-26.39***
Sri Lanka	0.596***	0.011	0.151***	36.53***	0.017	15.71	346.4***	-25.53***
Frontier	0.275*	0.008	-1.464***	18.59 ***	-0.014	204.9	782.3***	-22.51***

Notes: The daily returns is calculated as $r_t = ln(p_t) - ln(p_t)$. The superscripts '***',' **' and '*' denotes significant levels at 1%, 5% and 10%. The critical values at 1%, 5%, and 10% levels of the ADF test for unit root are -3.430, -2.860 and -2.570. Sharpe Ratio is measured as the ratio of excess return (risk premium) to the standard deviation of its excess returns (i.e. $\frac{r_p - r_f}{\sigma_p}$).

1.5 Findings and Discussions

In this session, we present results for efficient or adaptive nature of developed, emerging and frontier stock markets using return predictability tests and technical trading rules. The independence of stock returns are estimated using Wild Bootstrap Variance Ratio (WBAVR) and Automatic Portmanteau (AQ) tests. The AVR statistics indicate positive or negative autocorrelation in stock returns although empirical studies employ the absolute values, although irrespective of the direction of the signs, less autocorrelation implies higher efficiency (see Griffin *et al.*, 2010; Kim *et al.*, 2011).

The issue of market efficiency should not be treated as an all-or-nothing case but rather considered from the perspective that it evolves and varies over time. Based on the yearly subsample analysis, we can classify the markets as efficient, inefficient or adaptive. On the one hand, the market is efficient (inefficient) if returns are independent (dependent) throughout the subsamples. In addition, we consider a market to be sufficiently efficient if the returns are independent in the full sample based on WBAVR and AQ tests. On the other hand, the market is adaptive if returns have gone through the cyclical move between independence/unpredictability and dependence/predictability throughout the sample.

We measure the absolute/constant and relative/time-varying/dynamic return predictability of the 30 stock markets under scrutiny. It is good practice to compare the notion of absolute efficiency with relative efficiency in order to understand the dynamic nature of market efficiency. The absolute efficiency which is measured over a single period for a particular market does not capture the degree of market efficiency. Whereas, the relative efficiency measured in form of fixed-length rolling window or other techniques can detect dynamic return predictability overtime. Therefore, we expect that the degree of return predictability will vary over time due to possible changing market conditions, suggesting evidence of AMH.

Furthermore, we use the adaptive moving average (AMA) and moving average convergence divergence (MACD) rules to examine the economic significance of the predictive power and profitability for each markets. We compare these TTRs with the buy-and-hold strategy. In order to capture the changing efficiency and profitability of these markets, we carry out subsample analysis for the period of Great Moderation (GM) and Great Austerity (GA). The subsample analysis helps to monitor the stability of the technical trading rule performance and tackle the problem of data snooping bias (see Schulmeister, 2009; Park and Irwin, 2010; Ülkü and Prodan, 2013).[10] The main goal of this chapter is to empirically understand if return predictability can generate significant risk-adjusted profits for technical stock traders during tranquil and turbulent times and further analyse the drivers of technical rule profitability.

1.5.1 Constant and Absolute Return Predictability

We report the full and summary results of the WBVAR and AQ tests in Table 1.2, Table **1.3**, Table **1.4** and Table **1.5**. In Table 1.2, the WBVAR tests on the full period for the developed markets detect dependency or return predictability in UK, Germany, France and US, whereas return predictability was not found in Canada, Japan, Australia and Hong Kong. This suggests that the stock markets in the developed Pacific region are more efficient compare to Western Europe and US. In absolute terms, US and UK markets exhibit more return predictability based on linear dependence than other developed markets. Contrary to the above results, the AQ test results in Table 1.3 show that we could not reject the null hypothesis of return unpredictability in the conditional mean of the developed markets, except for US market. Consistent with the WBVAR test, this implies that the US market does not satisfy the weak-form efficiency in the full sample. In the emerging markets, we find return predictability in Russia, Poland, Mexico, Egypt and South Africa based on WBAVR and AQ tests. Furthermore, we detect strong linear dependency in all frontier markets using both tests, suggesting that these markets are highly inefficient. The Brazilian market indicates the most efficient market while the Nigerian market exhibits the most inefficient. Both tests also indicate return predictability in the specialised markets (MSCI developed, emerging and frontier markets, and Euro Area markets), therefore suggesting that internationally diversified markets do not satisfy the weak-form EMH.

Analysing GM and GA periods, the WBAVR and AQ tests indicate no return predictability throughout the yearly subsamples of Japan suggesting consistency with EMH. We also attribute market efficiency to markets that indicate no return predictability in the full sample although exhibit inefficiency in a single year. The markets that meet these criteria include Canada, Australia, Brazil, China and Turkey. Specifically, we attribute the efficiency in the Chinese market to 'price-limited reform' which limits daily stock price variation to at most 10% (5% for some special treated stocks) as well as capital control on foreign portfolio flows (see Wang *et al.,* 2010). This raises a question whether financial market control increases the degree of efficiency when compared with financial market liberalisation. We may argue that it all depends though, as the heavily liberalised Hong Kong market has a high degree of market efficiency,

[10] Data snooping arises when a given set of data is used more than once for purposes of inference or model selection (see Lo and Mackinlay, 1990; Sullivan *et al.,* 1998; White, 2000)

while the state-controlled Chinese market similarly indicates a high degree of efficiency. Interestingly, the evidence of market efficiency in Turkey corroborates with the findings of Lagoarde-Segot and Lucey (2008) that the Turkish stock market is more liquid and capitalised and has a well-developed financial system.

However, the MSCI emerging markets exhibit return predictability in all subsamples, suggesting market inefficiency. This implies that profit opportunities may exist from time to time in this specialised market. For all other markets, we detect an oscillation between dependence and independence in stock returns over time, consistent with the AMH paradigm. The cyclical move between dependence and independence, for instance in UK and US markets, corroborates with Urquhart and Hudson’s (2013) evidence of AMH (see also Ito and Sugiyama, 2009; Kim *et al.*, 2011; *Lim et al*., 2013).

In addition, the frontier markets have more periods of dependence than the emerging markets. For instance, the Egyptian market is the most inefficient among the emerging markets while the Nigerian market is the most inefficient among the frontier markets. We argue that the frontier markets adapt more slowly to efficiency unlike the emerging and developed markets. In contrast with existing evidence reported by Worthington and Higgs (2006) and Smith and Dyakova (2016), we did not find that Argentine market is consistent with the EMH.

We further demonstrate that the 2007/2008 stock market crash has led to violations of the weak-form efficiency in the UK, France, US, Egypt, Jamaica, Ukraine, Kenya, Nigeria, Sri Lanka, MSCI developed and emerging markets. The origin of the crisis began in the Western economies (US and UK) and spread to other countries in the globe, causing massive financial market disruptions. However, the impact of the 2008 financial crisis on departure from weak form efficiency is most significant in the US and UK stock markets. This shows from a different perspective that financial contagion occurred between the two markets. Similarly, the highest prevalence of return predictability among countries was in 2014/2015, during the intense period of the Eurozone debt crisis. This suggests that high degree of return predictability is prevalent during financial crisis. This is consistent with the findings of higher return predictability during crisis period as documented by Smith (2012) and Urquhart and Hudson (2013).

In summary, the WBAVR and AQ tests show relatively similar results except that the WBAVR test reports a higher probability of rejection of market efficiency. Following the argument of Charles *et al.* (2011), the use of the AVR is strongly recommended since it is mostly uncertain in practical applications whether the nature of dependency is linear or nonlinear.

Table 1.2: Wild Bootstrap Automatic Variance Ratio Test

		Great Moderation (05/03/1999 – 04/03/2007)								Great Austerity (05/03/2007 – 04/03/2015)							
Market	**Full**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
UK	-3.355*	0.413	-0.071	0.102	-0.386	-1.042	-0.967	-0.441	-1.045	-1.647*	-0.183	-0.554	-0.004	1.207	-1.308*	0.103	0.099
GER	-2.172*	0.747	-1.009	0.374	-0.455	-0.879	-0.471	-0.002	-0.544	-0.638	-0.050	-0.329	0.008	1.488*	-0.045	0.051	-0.246
FRA	-2.173*	1.273	-0.978	-0.046	0.025	-0.165	-1.267*	-0.219	-0.761	-1.257	-0.726	-0.478	-0.042	1.134	-1.335*	-0.617	-0.647
ITA	-0.568	-0.007	-1.165	0.399	-0.009	-0.589	0.002	-0.039	-1.571*	-1.027	-0.128	-0.041	0.447	0.516	-0.485	-0.392	-1.551*
US	-4.387*	-0.035	0.016	0.535	-0.436	-1.699*	0.446	-1.30*	0.609	-1.462*	-2.44*	-0.862	-0.542	-0.792	0.031	-0.331	-0.005
CAN	-0.464	1.173	0.417	0.453	-0.194	0.571	0.374	0.007	0.545	-0.595	-1.519	-0.210	-0.172	0.943	0.970	-0.086	0.315
JAP	-1.119	-0.709	0.789	-0.859	-0.667	0.616	-0.595	0.286	-0.027	-0.433	0.006	-0.327	0.003	-0.014	-0.114	-0.643	-0.739
HK	-0.451	1.008	0.009	0.042	-0.202	1.588*	0.019	0.445	0.284	-1.085	-0.571	0.013	-0.017	-0.039	-0.056	1.054*	0.093
AUS	-1.042	0.217	-0.172	-0.074	-0.763	-0.464	1.033	-0.169	-1.409*	0.012	-0.542	0.037	-0.491	0.378	-0.028	0.055	0.459
EURO	-2.172*	1.341*	-1.092	-0.078	-0.023	-0.731	-0.629	-0.072	-0.76	-1.192	-0.426	-0.357	0.073	1.008	-0.841	-0.500	-1.297
DEV	3.243*	2.447*	0.885	1.631*	1.297	0.773	1.978*	1.611*	2.754*	2.237*	0.054	1.247*	1.085	1.439[c]	1.245*	2.121*	2.873*
RUS	4.599*	2.427*	-0.549	0.689	1.172*	0.046	1.452*	1.069	0.222	0.479	2.093*	1.077*	1.094	2.402*	0.665	-0.858	0.843
POL	2.281*	-0.089	-0.693	1.518*	-0.044	1.900*	-0.013	0.445	2.161*	-0.015	0.871	0.970	-0.389	1.443	-0.349	0.963	1.045
MEX	2.364*	1.601*	0.881	1.658*	-0.011	0.861	1.264	0.439	1.310*	-0.052	0.882	1.628*	-0.076	-0.431	0.561	0.579	1.716*
BRZ	-0.034	1.107	0.477	0.261	0.442	0.504	0.194	0.241	0.327	-1.050	0.100	-0.365	-0.029	-0.498	-0.054	-0.578	-0.474
IND	1.86	-0.524	1.522[c]	1.085	0.025	1.622*	0.039	1.092*	0.792	1.051	0.139	0.589	-0.012	1.334*	-0.315	1.009	1.619*
CHI	-0.136	-0.079	0.552	-0.062	0.255	-0.098	-0.014	0.013	0.003	-0.002	-0.124	0.017	-0.072	-0.462	-0.601	1.428*	0.011
TUR	0.723	1.319	-0.496	0.589	-0.194	-0.685	0.829	0.616	0.107	-0.024	0.977	1.359*	-0.033	0.057	-0.027	-1.156	-0.285
EGY	8.269*	3.144*	1.775*	2.906*	1.679	2.239*	2.718*	0.416	3.167*	1.864*	2.792*	1.903*	1.503	1.294	1.119	1.664*	3.493*
SA	2.214*	2.915*	0.762	2.299*	1.065	2.085*	0.062	-0.173	-0.066	0.019	0.953	0.665	-0.397	0.454	-0.256	-0.823	-1.638*
EM	8.626*	4.363*	3.431*	4.342*	1.178*	3.278*	2.482*	2.419*	3.419*	2.369*	2.364*	2.278*	1.726*	2.966*	1.368*	2.656*	2.873*
ARG	3.188*	0.083	0.023	1.412	1.048	-0.587	1.157	0.437	0.425	-1.005	0.562	-0.326	0.223	1.905*	0.902	1.569*	-0.184
JAM	3.899 *	8.208*	4.051*	2.296*	-0.124	0.394	3.771*	2.401*	2.108*	-2.465*	-0.592	-0.678	-0.019	1.878*	-1.986*	-2.13*	-2.968*
ROM	3.334*	4.198*	0.629	0.336	1.309	4.124*	2.007*	0.427	0.551	0.931	1.155	1.228	-1.968	1.419	3.101*	-0.341	2.057*
UKR	6.925*	3.266*	0.627	-1.92*	-2.72*	-2.895*	-0.022	-1.165	5.870*	2.343*	3.363*	4.283*	4.379*	3.769*	5.354*	1.165	0.823
KEN	15.82*	2.370*	0.013	-0.152	6.131*	3.652*	-0.109	8.525*	8.901*	4.389*	7.018*	5.592*	6.107*	5.802*	6.059*	4.777*	1.674*
NIG	18.67*	8.430*	5.465*	-1.255	3.878*	5.167*	4.288*	5.157*	4.793*	7.614*	8.055*	5.638*	2.644*	1.420*	3.553*	1.318	5.662*
PAK	6.193*	0.795	0.014	-0.076	1.074	0.514	0.043	0.548	1.261	0.601	6.582*	0.112	0.958	0.208	0.001	2.766*	1.852*
SRL	7.659*	5.507*	1.312	1.591	2.707*	0.184	1.281	1.849	1.139	2.867*	2.194*	4.345*	2.627*	1.664*	4.078*	2.250*	4.287*
FM	11.25*				-0.288	0.442	4.455*	0.044	1.018	2.103	3.570*	3.116*	1.742*	2.419*	3.164*	1.804*	4.540*

Notes: The superscript ‘*’ denotes significant level at 10%. The AVR test is based on wild bootstrapping of 500 iterations.

Table 1.3: Automatic Portmanteau (AQ) Test

		Great Moderation (05/03/1999 – 04/03/2007)								Great Austerity (05/03/2007 – 04/03/2015)							
Markets	Full	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
UK	2.598	0.395	0.265	0.009	1.231	0.806	3.888*	0.739	0.983	4.901*	0.352	1.939	0.000	1.486	3.254*	0.039	0.049
GER	0.564	0.453	3.307*	0.221	1.005	1.931	0.355	0.029	0.562	0.380	0.310	0.862	0.000	4.041*	0.041	0.018	0.372
FRA	1.958	2.423	2.798*	0.033	0.002	0.067	5.792*	0.572	0.912	2.951*	1.158	1.129	0.024	1.729	2.936*	0.824	0.699
ITA	0.554	0.018	3.309*	0.099	0.007	0.636	0.026	0.135	4.448*	2.814*	0.047	0.214	0.315	0.353	0.638	0.516	4.386*
US	8.745*	0.001	0.069	0.483	0.501	7.017*	0.500	3.593*	8.115*	5.184*	4.599*	2.537	0.793	1.634	0.009	0.509	0.001
CAN	0.199	0.897	0.415	1.292	0.152	0.009	0.326	0.066	1.255	0.524	1.358	0.466	0.240	1.307	2.745*	0.104	0.329
JAP	0.967	1.490	0.809	1.488	1.473	0.814	0.769	0.007	0.012	0.353	0.001	0.398	0.006	0.000	0.325	2.432	1.237
HK	0.151	1.378	0.000	0.113	0.239	5.273*	0.006	0.402	0.247	0.582	0.483	0.057	0.093	0.000	0.208	5.557*	0.111
AUS	0.979	0.067	0.158	0.013	1.459	0.514	0.673	0.342	4.149*	0.000	0.973	0.103	0.654	0.371	0.028	0.018	0.284
EURO	1.967	2.426	3.537*	0.149	0.059	0.731	1.842	0.244	0.859	2.401	0.825	0.741	0.094	2.212	1.354	0.548	1.584
DEV	19.07*	10.74*	5.389*	5.285*	2.043	0.228	6.295*	3.308*	11.18*	5.113*	0.946	1.046	2.094	1.754	3.681*	5.644*	6.500*
RUS	14.52*	8.759*	0.635	0.689	4.074*	0.809	2.294	1.088	0.159	0.495	3.271*	1.529	1.066	5.329*	1.070	0.388	0.537
POL	8.967*	0.127	0.714	3.797*	0.098	2.777*	0.000	0.093	4.644*	0.033	2.307	3.107*	0.349	2.430	0.741	0.793	4.555*
MEX	26.20*	5.644*	3.976*	10.85*	0.014	0.813	1.197	0.247	6.079*	0.041	1.599	3.638*	0.051	0.142	0.642	0.560	5.053*
BRZ	0.000	0.742	0.403	0.109	0.452	0.048	0.109	0.077	0.419	4.707*	0.029	0.819	0.109	0.194	0.079	0.713	0.435
IND	5.021*	0.899	2.850*	1.724	0.045	1.919	0.137	3.219*	0.415	0.518	0.036	0.606	0.075	2.697	0.271	2.555	6.027*
CHI	0.016	0.072	0.383	0.009	0.182	0.104	0.012	0.031	0.230	0.001	0.211	0.004	0.018	0.462	1.431	3.887*	0.092
TUR	0.202	0.919	0.319	0.319	0.663	0.179	0.369	1.175	0.673	0.006	0.034	2.344	1.038	0.055	0.025	0.009	0.115
EGY	32.52*	11.35*	6.276*	11.04*	0.001	0.126	4.332*	0.077	3.164*	1.109	3.434*	5.427*	0.897	2.441	2.146	2.235	7.317*
SA	4.128*	7.886*	0.198	4.214*	1.056	4.969*	0.026	0.796	0.067	0.021	0.742	0.409	0.312	0.455	7.527*	0.208	3.377*
EM	64.91*	20.88*	5.074*	25.12*	3.149*	8.849*	9.593*	8.937*	10.75*	7.298*	6.149*	8.221*	2.898*	13.29*	3.209*	13.98*	13.81*
ARG	5.691*	0.000	0.486	2.747*	1.722	1.409	1.305	0.521	0.544	1.387	0.359	1.186	0.049	1.984	1.215	3.003*	0.002
JAM	3.152*	14.52*	1.780	3.735*	8.447*	0.301	8.990*	2.225	3.695*	3.251*	0.685	0.002	0.012	9.730*	2.208	6.808*	8.836*
ROM	10.03*	8.606*	1.168	0.105	2.069	8.095*	3.677*	0.147	0.579	1.539	0.783	0.863	1.758	1.390	6.908*	0.252	4.220*
UKR	11.71*	12.68*	0.697	4.319*	5.623*	10.43*	0.037	3.073*	10.22*	7.439*	5.478*	6.545*	6.302*	12.73*	24.59*	4.348*	1.378
KEN	18.46*	1.429	0.076	0.228	23.56*	1.489	0.024	60.24*	48.80*	8.793*	33.07*	17.74*	26.02*	21.78*	39.84*	8.278*	4.827*
NIG	283.5*	31.59*	7.550*	0.409	21.58*	28.89*	26.97*	12.89*	27.39*	31.71*	123.9*	31.98*	16.17*	2.193	4.933*	1.368	24.75*
PAK	15.21*	0.363	0.013	0.000	1.388	0.003	0.050	0.854	1.149	0.216	21.16*	0.001	1.003	0.232	0.204	6.809*	6.457*
SRL	22.15*	29.88*	1.566	3.189*	3.436*	0.751	1.700	2.536	0.583	8.364*	1.223	6.903*	0.877	7.900*	8.911*	2.616	5.074*
FM	29.99*				0.218	0.001	18.13*	0.049	1.597	0.792	2.258	8.172*	2.712*	3.233*	6.126*	1.986	11.71*

Notes: The superscript '*' denotes significant level at 10%. The AQ statistics is an asymptotic test and follow the chi-square distribution with one degree of freedom

Table 1.4: Summary of WBAVR Results

		Great Moderation (05/03/1999 – 04/03/2007)								**Great Austerity (05/03/2007 – 04/03/2015)**								**Classification**
Markets	Full	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
UK	D	I	I	I	I	I	I	I	I	D	I	I	I	I	D	I	I	Adaptive
GER	D	I	I	I	I	I	I	I	I	I	I	I	I	D	I	I	I	Adaptive
FRA	D	I	D	I	I	I	D	I	I	D	I	I	I	I	D	I	I	Adaptive
ITA	I	I	I	I	I	I	I	I	D	I	I	I	I	I	I	I	D	Adaptive
US	D	I	I	I	I	D	I	D	I	D	D	I	I	I	I	I	I	Adaptive
CAN	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Efficient
JAP	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Efficient
HK	I	I	I	I	I	D	I	I	I	I	I	I	I	I	I	D	I	Adaptive
AUS	I	I	I	I	I	I	I	I	D	I	I	I	I	I	I	I	I	Adaptive
EURO	D	D	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Efficient
DEV	D	D	I	D	I	I	D	D	D	D	I	D	I	D	D	D	D	Adaptive
RUS	D	D	I	I	D	I	D	I	I	I	D	D	I	D	I	I	I	Adaptive
POL	D	I	I	D	I	D	I	I	D	I	I	I	I	I	I	I	I	Adaptive
MEX	D	D	I	D	I	I	I	I	D	I	I	D	I	I	I	I	D	Adaptive
BRZ	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Efficient
IND	D	I	D	I	I	D	I	D	I	I	I	I	I	D	I	I	D	Adaptive
CHI	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	D	I	Efficient
TUR	I	I	I	I	I	I	I	I	I	I	I	D	I	I	I	I	I	Efficient
EGY	D	D	D	D	I	D	D	I	D	D	D	D	I	I	I	D	D	Adaptive
SA	D	D	I	D	I	D	I	I	I	I	I	I	I	I	I	I	D	Adaptive
EM	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	Inefficient
ARG	D	I	I	I	I	I	I	I	I	I	I	I	I	D	I	D	I	Adaptive
JAM	D	D	D	D	I	I	D	D	D	D	I	I	I	D	D	D	D	Adaptive
ROM	D	D	I	I	I	D	D	I	I	I	I	I	I	I	D	I	D	Adaptive
UKR	D	D	I	D	D	D	I	I	D	D	D	D	D	D	D	I	D	Adaptive
KEN	D	D	I	I	D	D	I	D	D	D	D	D	D	D	D	D	D	Adaptive
NIG	D	D	D	I	D	D	D	D	D	D	D	D	D	I	D	I	D	Adaptive
PAK	D	I	I	I	I	I	I	I	I	I	D	I	I	I	I	D	D	Adaptive
SRL	D	D	I	I	D	I	I	I	I	D	D	D	I	D	D	D	D	Adaptive
FM	D				I	I	D	I	I	I	I	D	D	D	D	D	D	Adaptive

Notes: I and D represent independence and dependence of returns, respectively.

Table 1.5: Summary of AQ Results

		Great Moderation (05/03/1999 – 04/03/2007)								Great Austerity (05/03/2007 – 04/03/2015)								Classification
Markets	Full	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	
UK	I	I	I	I	I	I	D	I	I	D	I	I	I	I	D	I	I	Adaptive
GER	I	I	I	I	I	I	I	I	I	I	I	I	I	D	I	I	I	Adaptive
FRA	I	I	D	I	I	I	D	I	I	D	I	I	I	I	D	I	I	Adaptive
ITA	I	I	D	I	I	I	I	I	D	D	I	I	I	I	I	I	D	Adaptive
US	D	I	I	I	I	D	I	D	D	D	D	I	I	I	I	I	I	Adaptive
CAN	I	I	I	I	I	I	I	I	I	I	I	I	I	I	D	I	I	Efficient
JAP	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Efficient
HK	I	I	I	I	I	D	I	I	I	I	I	I	I	I	I	I	D	Adaptive
AUS	I	I	I	I	I	I	I	I	D	I	I	I	I	I	I	I	I	Efficient
EURO	I	I	D	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Adaptive
DEV	D	D	D	D	I	I	D	D	D	D	I	I	I	I	D	D	D	Adaptive
RUS	D	D	I	I	D	I	I	I	I	I	D	I	I	D	I	I	I	Adaptive
POL	D	I	I	D	I	D	I	I	D	I	I	D	I	I	I	I	D	Adaptive
MEX	D	D	D	D	I	I	I	I	D	I	I	D	I	I	I	I	D	Adaptive
BRZ	I	I	I	I	I	I	I	I	I	D	I	I	I	I	I	I	I	Efficient
IND	D	I	D	I	I	I	I	D	I	I	I	I	I	I	I	I	D	Adaptive
CHI	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	D	Efficient
TUR	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	Efficient
EGY	D	D	D	D	I	I	D	I	D	I	D	D	I	I	I	I	D	Adaptive
SA	D	D	I	D	I	D	I	I	I	I	I	I	I	I	D	I	D	Adaptive
EM	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	D	Inefficient
ARG	D	I	I	D	I	I	I	I	I	I	I	I	I	I	I	I	D	Adaptive
JAM	D	D	I	D	D	I	I	D	I	D	I	I	I	D	I	D	D	Adaptive
ROM	D	D	I	I	I	D	D	I	I	I	I	I	I	I	D	I	D	Adaptive
UKR	D	D	I	D	D	D	I	D	D	D	D	D	D	D	D	D	D	Adaptive
KEN	D	I	I	I	D	I	I	D	D	D	D	D	D	D	D	D	D	Adaptive
NIG	D	D	D	I	D	D	D	D	D	D	D	D	D	I	D	I	D	Adaptive
PAK	D	I	I	I	I	I	I	I	I	I	D	I	I	I	I	I	D	Adaptive
SRL	D	D	I	D	D	I	I	I	I	D	I	D	I	D	D	I	D	Adaptive
FM	D				I	I	D	I	I	I	I	D	D	D	D	I	D	Adaptive

Notes: I and D represent independence and dependence of returns, respectively.

1.5.2 *Dynamic and Relative Market Efficiency*

Focusing on WBAVR test, Figure 1.2 demonstrates the *p*-values of the test in a two-year rolling estimation window in order to capture the time variation in stock return predictability of the markets under scrutiny. The *p*-values shown in the graph at 5% significant level indicates rejection of the null hypothesis of serial uncorrelatedness if below the dotted line. This suggests the presence of return predictability or linear dependency or market inefficiency.

The choice of this window length is consistent with the similar choice made by Belaire-Franch and Opong (2005), Hung (2009), Kim *et al.* (2011) and Smith and Dyakova (2016). According to Smith and Dyakova (2016), a two-year fixed window length is sufficiently short to capture short-lived significant return predictability. The choice of this window would prevent the statistical test from size distortion or inadequate power. In this case, the first window starts on 5 March 1999 and ends on 5 March 2001. The changes in market efficiency is being captured by the fixed-length rolling window, which enables us to further capture historical episodes coinciding with departures from weak-form efficiency.

There is a clear evidence from the graphical display that the nature of return predictability is time-varying due to changing market conditions, hence may create opportunities for profits to be exploited by investors. This is consistent with the AMH framework, which alludes that market efficiency is characterised by an evolutionary process over time and across markets. Overall, there is a low degree of return predictability in the developed markets unlike the rapidly changing return predictability evident in the frontier markets. The stock returns of the Egyptian market is the most predictable among emerging markets, suggesting that the market is less efficient. Similarly, the stock returns of MSCI emerging and frontier markets are highly predictable while that of MSCI developed and Euro Area markets are less predictable.

The periods of intense time-varying return predictability can be linked to major exogenous events. For instance, the occurrence of intense capital outflows in emerging markets and global financial crisis between 2006 and 2008, significantly increases time-varying return predictability in almost all the markets, particularly the developed and emerging countries. Similarly, the 2012-2014 severe Eurozone debt crisis triggers a rise in return predictability in most European countries. Indeed, most periods of return predictability can be linked to various episodes, implying that investors' reactions to information is time-varying. According to Timmermann (2008), the evolution of return predictability through time is caused by incomplete learning effects, structural changes in the return generating process and exogenous events. These results on return predictability are consistent with the findings of Diebold and Yilmaz (2009), Kim *et al*. (2011), Smith and Dyakova (2016), although they investigated few developed and emerging markets.

We summarise the results of the degree of return predictability for the full and sub-periods in Table 1.6. The stock markets are ranked by relative efficiency from the most efficient to the least efficient. The *z*-test statistics test the hypothesis that the degree of return predictability is the same in the two subsamples (GM and GA periods).

$$z = \frac{\hat{p}_2 - \hat{p}_1}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_2}+\frac{1}{n_1}\right)}} \sim N(0,1) \tag{1.21}$$

where $\hat{p}$ is the proportion of rolling window WBVAR test rejecting the random walk hypothesis at the 5% significant level; $\hat{p}_1$ and $\hat{p}_2$ are the sample proportions in GM period (2001 – 2007) and GA (2007 – 2013); n_1 and n_2 are the sample sizes. We conjecture that the market is less predictable or more weak-form efficient on average in the GA period than GM period if the test statistic is positive and significant.

The results show that the test statistic is positive in 18 out of 30 markets and negative in 12 out of 30 markets. This suggests that return predictability falls in 60% of the markets during the GA period, hence strengthening the weak-form market efficiency in majority of markets. On the basis of statistical significance, 7 out of 30 markets have become less efficient, while 5 out of 30 markets have become more efficient. Particularly, return predictability increases for many frontier markets, which suggests that markets in Argentina, Ukraine, Kenya, Nigeria, Kenya and Pakistan have become less efficient in turbulent times. The increased market inefficiency of these markets may be attributed to increasing market frictions common to immature markets.

Over the full period, the US market has the highest rank of return unpredictability with 97.59% of the WBAVR test, hence the market is the most informationally efficient on the basis of time-variation. Most developed markets have lower degree of return predictability though the degree of predictability in Australia is higher than some emerging and frontier markets such as China, Poland, Brazil and Argentina. Likewise, the return unpredictability rate of 96.09% in the UK is also lower than the above markets except for Argentina. The most predictable and informationally inefficient markets are prevalent in frontier markets. For instance, Kenya has the lowest ranking of unpredictability with 60.25% of the WBAVR test.

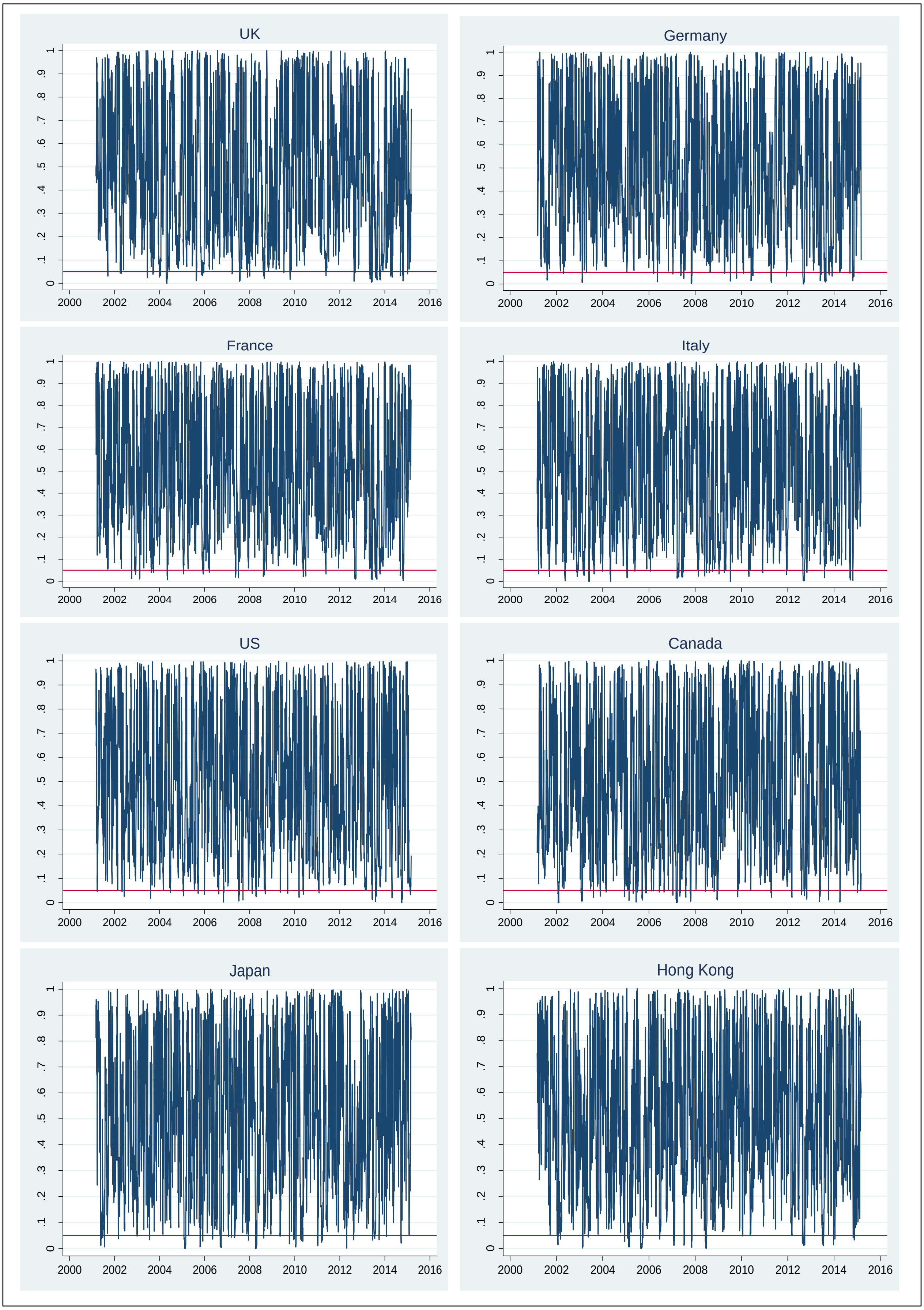
During the GM period, the German market has the highest rank of least return predictability with 98.72%, followed by US market with 98.53%. However, the US and UK markets jump to highest rank of least predictability with 97.83% during GA period. Remarkably, the Brazilian market that ranks 13th in return unpredictability in GM period, improved tremendously to rank 3rd in GA period. This remarkable improvement in informational efficiency was also achieved by South African market moving from the rank of 17th in GM period to 7th in GA period. The Polish market exhibits the most dramatic rise in return predictability, hence her rank falls from 5th in GM period to 18th in GA period. Perhaps, the Eurozone debt crisis has reduced the informational efficiency of the Polish market. The markets that have maintained the same rank in both periods, include Canada, Australia, diversified Euro Area (Eurostoxx), Russia, Turkey, Egypt, Kenya, Nigeria, MSCI emerging and frontier markets. The Kenyan and Nigerian markets similarly show the most predictable markets during the GM and GA periods.

In conclusion, we find strong evidence that most markets go through a cyclical sequence of predictability and unpredictability, consistent with the theory of AMH. Thus, investors can identify and exploit market inefficiencies in many frontier and some emerging markets with the aim of providing compelling risk-adjusted returns over the long term, unlike the less return predictability prevalent in the developed markets. The developed markets have the highest degree of market efficiency, followed by the emerging markets, while most frontier markets are informationally inefficient. The biggest improvement in efficiency are the Brazilian and South African markets, while the highest deterioration in efficiency are the Polish and Argentine markets. These results in relation with AMH are consistent with the findings of Lim and Brooks (2009), Griffin *et al*. (2010), Lim *et al.* (2011), Smith and Dyakova (2016). Although, these studies are based on different methodologies and limited datasets. Overall, a single overarching result suggests that the AMH provides a better description than EMH of the behaviour of stock returns, particularly in emerging and frontier markets. These results have major implications on portfolio investors who may utilise technical analysis to exploit profit opportunities on the basis of the evolutionary nature of market efficiency.

Table 1.6: Market Ranking by Return Unpredictability

Market	Full period		GM		GA		Z-test
	WBVAR* ($\hat{p}$)	**Rank**	**WBVAR* $\hat{p}_1$**	**Rank**	**WBVAR* $\hat{p}_2$**	**Rank**	
UK	96.09	12	96.74	6	97.83	1	1.566
GER	97.21	4	98.72	1	96.81	8	-3.254*
FRA	97.32	3	98.08	4	97.45	5	-1.106
ITA	96.17	11	96.23	10	95.59	13	-0.838
US	97.59	1	98.53	2	97.83	1	-1.282
CAN	96.55	5	96.49	9	96.55	9	0.098
JAP	96.49	7	96.10	11	96.42	10	0.486
HK	96.44	8	95.53	12	97.32	6	2.701*
AUS	95.51	14	95.15	14	95.15	14	0.000
EURO	97.51	2	98.21	3	97.51	3	-1.261
DEV	91.81	20	92.02	19	92.34	22	0.326
RUS	94.33	18	93.99	17	94.38	17	0.464
POL	96.22	10	97.19	5	94.06	18	-4.592*
MEX	95.32	15	95.02	15	96.42	10	1.861
BRZ	96.25	9	95.21	13	97.51	3	3.858*
IND	93.27	19	90.36	21	95.21	15	5.419*
CHI	96.52	6	96.67	7	96.42	10	-0.390
TUR	94.94	16	94.76	16	95.15	16	0.489
EGY	85.87	24	85.31	24	85.63	24	0.257
SA	94.53	17	91.06	20	97.06	7	7.383*
EM	81.85	27	80.01	28	81.55	28	1.113
ARG	95.59	13	96.68	8	93.81	19	-3.917*
JAM	87.29	23	81.48	26	93.49	20	10.09*
ROM	89.63	21	86.39	23	92.46	21	5.567*
UKR	82.43	26	88.38	22	81.67	27	-4.929*
KEN	60.25	30	68.84	30	51.09	30	-10.15*
NIG	64.36	29	68.90	29	57.15	29	-6.865*
PAK	89.59	22	92.46	18	87.93	23	-4.156*
SRL	77.66	28	80.20	27	82.69	26	1.759
FM	82.89	25	82.85	25	83.26	25	0.210

Notes: WBAVR* expresses the percentage of test statistics rejecting the random walk hypothesis or weak form hypothesis at the 5% significant level. The *Z*-test is used to test the hypothesis that is the same in the two subsamples. The 5% critical value is 1.96.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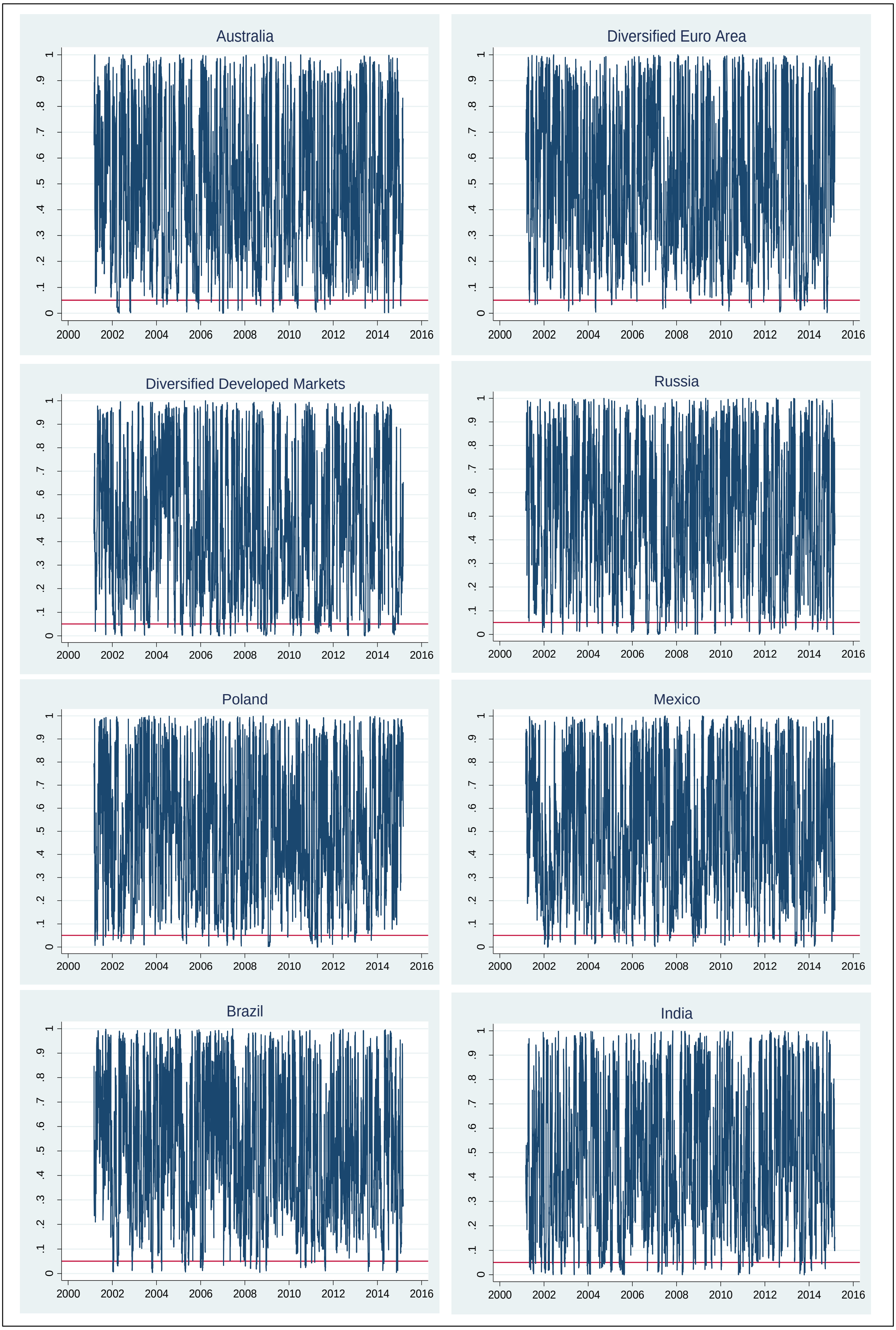
Australia
Diversified Euro Area
Diversified Developed Markets
Russia
Poland
Mexico
Brazil
India
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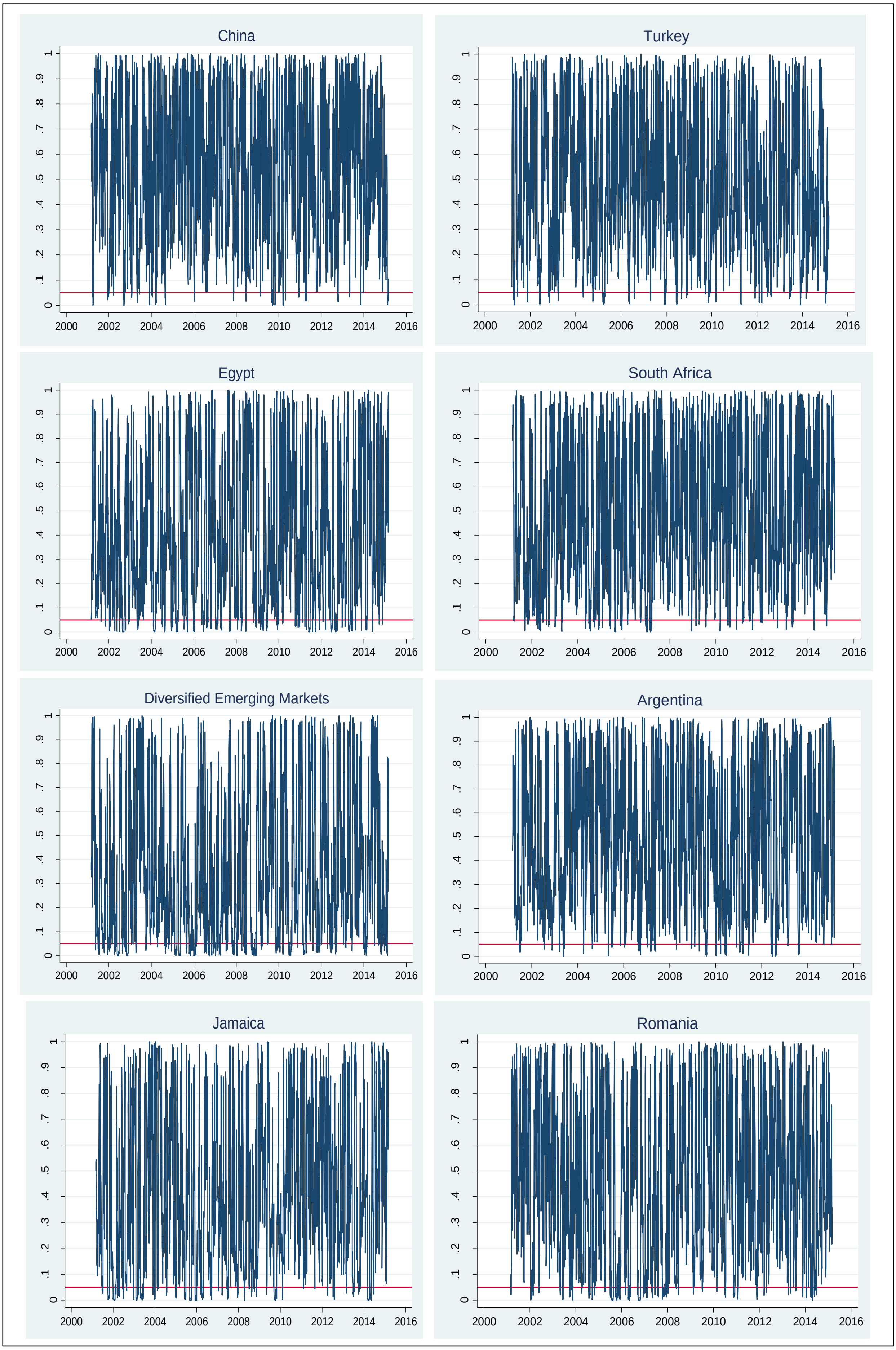
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Turkey
Egypt
South Africa
Diversified Emerging Markets
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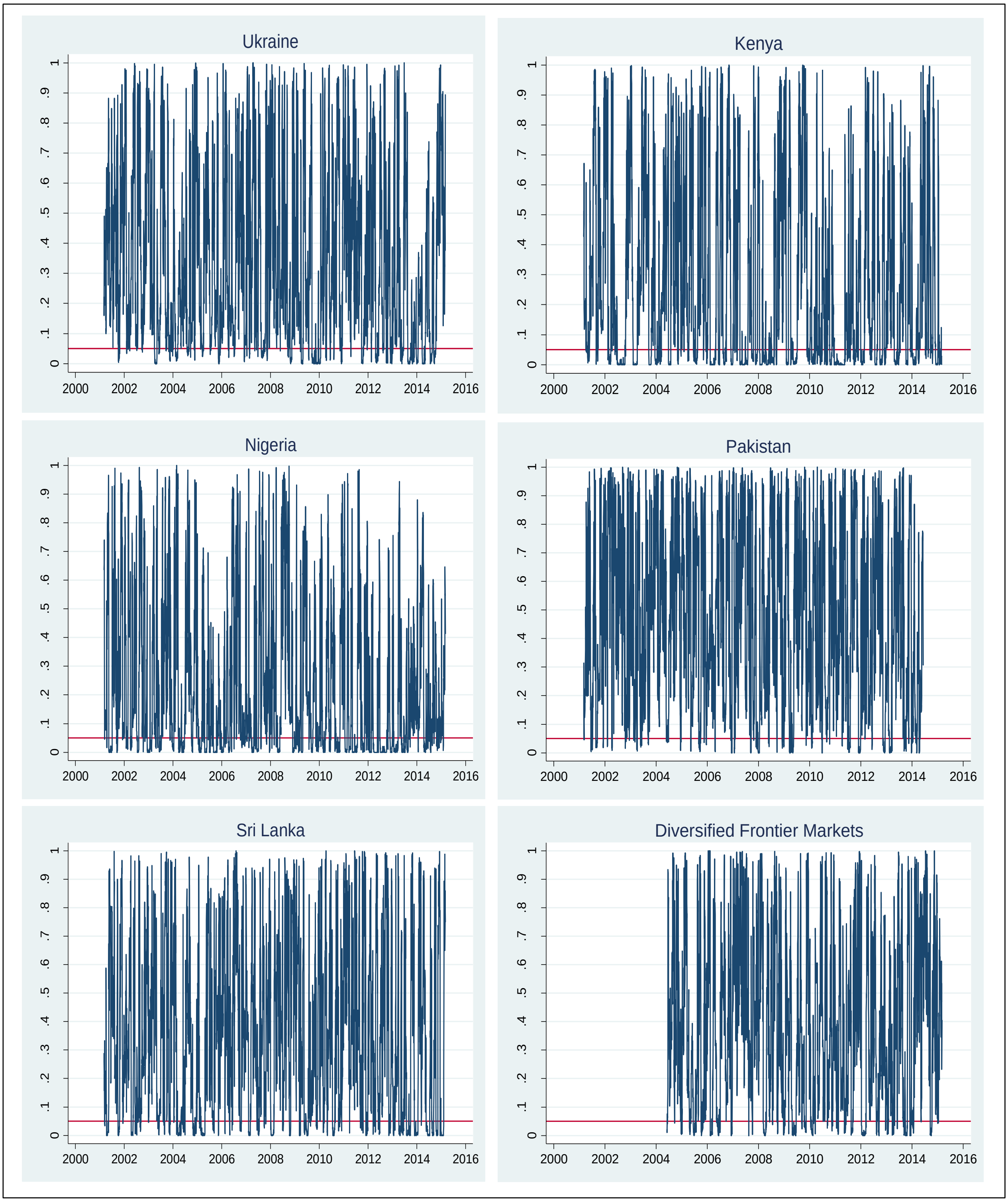


Figure 1.2: P-values of Rolling Window WBAVR Tests

1.5.3 *Testing the Predictive Power of AMA and MACD Trading Rules*

The preceding section finds evidence of absolute and dynamic return predictability mostly in emerging and frontier markets, implying that the re-occurrence of past patterns would make the use of technical analysis a feasible technique for active portfolio management. In this section, we aim to examine whether such departures from the EMH could be profitably exploited using technical trading strategies. We hypothesize that technical trading rules have no predictive ability on potential abnormal profits. We report the predictive performance of the AMA and MACD rules for the full sample and sub-periods. The rationale for the choice of these trading rules is to avoid whipsaw losses generated by false trading signals in a ranging or trending markets.

We follow the assumption in previous studies that technical signals generated are executed at the closing price of the day (see Metghalchi *et al.*, 2012; Ülkü and Prodan, 2013). The subsample analysis will check the consistency of results and draw implication for performance of trading rules during tranquil and crisis periods. We hypothesize that for the trading rules to exhibit predictive ability, the mean daily returns generated by the buy (sell) signals are positive (negative) and statistically significantly different from the unconditional buy-and-hold (BH) returns.

To begin with, Table 1.7 reports the results of the AMA trading rule for the developed, emerging and frontier markets in the full period. We find that 1 emerging market (Egypt) and 5 frontier markets (Ukraine, Kenya, Nigeria, Sri Lanka and MSCI frontier markets) indicate positive buy returns and are significantly different from the unconditional BH strategy. However, the AMA rule for sell signals is statistically stronger than the buy signals for a wide range of emerging and frontier markets, plus 4 developed markets, therefore suggesting that the sell signals have strong profit potential. Likewise, the sell signals generate higher average returns but lower standard deviation compared to the average returns and standard deviation generated by the buy signals. This suggests that the sell signals deliver a better return-to-volatility ratio (Sharpe ratio). This contrasts with the evidence of MACD and MA buy signals delivering a better return-to-volatility ratio reported by Ülkü and Prodan (2013). In addition, the buy returns are significantly different from the same period of sell returns in Euro Area markets (Euro Stoxx), 8 emerging markets and all frontier markets, suggesting that technical trading rules produce useful trading signals.

Similarly, Table 1.8 reports that the MACD rule for the sell signals are more statistically significant than the buy signals in all emerging and frontier markets, suggesting stronger predictive ability in these markets. Similar to AMA strategy, the sell signals deliver a better return-to-volatility ratio than the buy signals. On average, the buy signals generate over 50% signals compare to the sell signals in all markets, suggesting an upward market trend. The buy returns are significantly different from the sell returns in 8 out of 10 emerging markets and all frontier markets, indicating that the technical trading rules produce useful trading signals.

On the whole, both the AMA and MACD strategies consistently show that buy returns are significantly different from the same period of sell returns, predominantly in emerging and frontier markets. This supports the evidence that technical trading strategies generate useful trading signals (see Brock *et al.*, 1992; Fang *et al*., 2014). In comparative terms, the sell strategy has far more profit potential than the buy strategy, especially in the emerging and frontier markets. It is important to note also that the MACD rules produce less trading signals compare to AMA rules implying less predictive ability of the MACD rule. Overall for both trading strategies, we find 8(42) groups of buy(sell) signals producing higher than the BH returns at 10% significant level. Unlike the MACD rule producing 2(19) group of buy(sell) signals, the AMA rules generate 6(23) groups of buy(sell) signals higher than the BH returns at 10% significant level. Also, the AMA rules generate more trading signals across all markets, with an average of 224.4 trading signals per year, compared with only 128.6 signals per year generated by MACD rules. We conclude that the AMA strategy is relatively consistent with the MACD strategy although the former outperforms the latter.

Turning to subsample analysis, Table 1.9 reports the results of the AMA trading rule during the GM period. It shows that the positive buy returns of the AMA rule for Kenya and Nigeria are significantly different from the BH returns, respectively. However, the AMA rule for sell signals is significantly stronger than the buy signals for all emerging and frontier markets, plus 3 developed markets, therefore suggesting that sell signals generate strong profit potential. The return-to-volatility ratio is higher for sell signals when compared with buy signals. In most markets, the number of buy days far outweighs the sell days for both trading rules, indicating a rising market trend. The buy-sell differences are significantly different from zero in all frontier markets except Argentina, 8 emerging markets and 2 developed markets.

Additionally, Table 1.10 reports the MACD rule during the GM period. The results indicate that the sell signals are significantly stronger than the buy signals for all emerging and frontier markets, plus 2 developed markets, therefore suggesting stronger profit potential for the sell signals. The buy-sell differences are significantly different from zero in all emerging markets except Turkey and all frontier markets, suggesting that technical trading rules produce useful trading signals. Largely, the results of the MACD and AMA rules are consistent and are quite compelling in period of stability.

In another case, Table 1.11 reports the AMA trading rule for the GA period. Our results show that 1 emerging market (Egypt), and 5 frontier markets (Ukraine, Kenya, Nigeria, Sri Lanka and MSCI frontier markets), indicate positive buy returns and are significantly different from the unconditional BH strategy. Whereas, the AMA trading rule for the negative sell returns indicate 4 emerging and 7 frontier markets are significantly difference from the unconditional BH strategy. Comparing GA period with GM, the sell signals have less strong profit potential, whereas the buy signals have more profit potentials. The buy-sell differences are significantly different from zero in MSCI developed markets, 5 emerging markets and all frontier markets except Jamaica. This suggests that technical trading rules generate useful trading signals in these markets, although much less than GM period.

Table 1.12 reports the results of the MACD rule in the GA period. We find that Ukraine, Nigeria and MSCI frontier markets have positive buy returns that are significantly different from the BH returns, while markets in Turkey, Egypt, Argentina, Ukraine, Kenya, Pakistan and Sri Lanka have negative sell returns that are significantly different from the BH returns. The sell days generate more signals than the buy days, suggesting that we are out of the market during volatile times. The buy-sell differences are significantly different from zero in 4 emerging markets and all frontier markets, suggesting that technical trading rules generate useful trading signals.

Summarising the results of GM and GA periods for both trading strategies, we find 2(43) groups of buy(sell) signals producing higher than the BH returns during the GM period while 9(18) groups of buy(sell) signals generating higher than the BH returns during the GA period. Generally, we consistently find that the technical trading strategies for wide range of emerging and frontier markets yield strong potential profits, unlike the extremely low potential profits in the developed markets. However, the AMA rules are largely consistent with the MACD rules, although the AMA strategy outperform the MACD strategy in predictive ability.

In conclusion, these results are in line with the existing evidence on the predictive ability of technical rules in few markets as documented by Ratner and Leal (1999), Fifield *et al.* (2005), Yu *et al*., (2013), Fang *et al.* (2014). Technical rules have very low predictive power in Western European and North American countries. We discover a deterioration in the profit potential of the sell signals in the GA period, whereas the profit potential of the buy signal improve in the same period. The less predictive power generated by technical trading strategies during the GA period can be attributed to the improved market efficiency despite the rapidly changing market conditions. The improved market efficiency in GA period support the dynamic return predictability reported in Table 1.6. Nonetheless, profit potentials exist in some emerging and most frontier markets, hence casting further doubts on the weak-form efficiency of these markets. The results support the notion that trading rules exploit considerable information from the past to predict future stock prices movements in these markets, which is consistent with the AMH.

Table 1.7: Full period – AMA Trading Rule

Mkts	N_b	**Mean Buy ($*10^{-3}$)**	**t-stat**	SD_b	RV_b	N_s	**Mean Sell ($*10^{-3}$)**	**t-stat**	SD_s	RV_s	**Buy-sell ($*10^{-3}$)**	**t-stat**
Panel A: Developed Markets												
UK	2145	-0.081	-0.515	0.010	-0.001	1523	0.089	0.789	0.007	0.013	-0.171	-0.953
GER	2193	-0.004	-0.019	0.013	-0.000	1480	-0.263	-1.724^{*}	0.010	-0.026	0.259	1.166
FRA	2194	-0.081	-0.402	0.012	-0.001	1523	0.084	0.604	0.009	0.001	-0.165	-0.754
ITA	2077	0.197	1.014	0.013	0.015	1611	-0.007	-0.005	0.009	-0.000	0.198	0.889
US	2154	-0.114	-0.691	0.011	-0.010	1499	-0.046	-0.405	0.007	-0.001	-0.068	-0.363
CAN	2331	0.014	0.095	0.009	0.000	1331	-0.214	-1.916^{*}	0.007	-0.031	0.228	1.362
JAP	1862	-0.054	-0.279	0.012	0.000	1695	-0.012	-0.082	0.009	-0.000	-0.042	-0.189
HK	1975	0.039	0.208	0.012	0.000	1587	-0.297	-1.962^{**}	0.009	-0.030	0.337	1.506
AUS	2196	-0.020	-0.158	0.008	-0.000	1504	-0.155	-1.644	0.006	-0.026	0.135	0.923
EURO	2212	0.155	1.146	0.009	0.017	1521	-0.224	-2.224^{**}	0.007	-0.032	0.379	2.520^{**}
DEV	2127	-0.077	-0.398	0.013	-0.001	1570	-0.054	-0.392	0.009	-0.001	-0.023	-0.105
Panel B: Emerging Markets												
RUS	2037	0.302	0.748	0.026	0.001	1521	-0.936	-2.166^{**}	0.027	-0.034	1.238	3.612^{***}
POL	2146	0.094	0.624	0.010	0.000	1510	-0.497	-3.411^{***}	0.009	-0.055	0.590	3.072^{***}
MEX	2305	-0.099	-0.596	0.011	-0.001	1340	-0.516	-3.512^{***}	0.009	-0.057	0.416	2.064^{**}
BRZ	1988	-0.004	-0.019	0.015	-0.000	1649	-0.324	-1.761^{**}	0.012	-0.027	0.319	1.199
IND	2166	-0.017	-0.089	0.012	-0.000	1448	-0.500	-3.223^{***}	0.010	-0.050	0.483	2.098^{**}
CHI	1742	0.238	1.283	0.012	0.019	1762	-0.482	-2.913^{***}	0.011	-0.044	0.720	3.179^{***}
TUR	2070	0.024	0.088	0.018	0.000	1579	-0.803	-3.287^{***}	0.016	-0.050	0.827	2.454^{**}
EGY	1999	0.511	2.528^{**}	0.013	0.039	1566	-1.157	-6.482^{***}	0.012	-0.096	1.667	6.591^{**}
SA	2395	-0.150	-1.042	0.009	-0.017	1249	-0.410	-3.150^{***}	0.008	-0.051	0.260	1.454
EM	2174	0.241	1.544	0.010	0.024	1569	-0.585	-4.719^{***}	0.008	-0.073	0.825	4.621^{***}
Panel C: Frontier Markets												
ARG	1928	-0.088	-0.348	0.016	-0.001	1640	-0.722	-3.262^{***}	0.014	-0.052	0.634	2.026^{**}
JAM	1985	0.069	0.874	0.005	0.014	1591	-0.459	-5.125^{***}	0.006	-0.077	0.529	4.686^{***}
ROM	2106	0.127	0.629	0.013	0.001	1447	-0.853	-4.541^{***}	0.012	-0.071	0.979	3.834^{***}
UKR	1845	0.510	2.413^{**}	0.014	0.036	1734	-1.309	-6.412^{***}	0.013	-0.101	1.819	6.719^{***}
KEN	1817	0.672	6.397^{***}	0.007	0.096	1655	-0.819	-8.609^{***}	0.006	-0.137	1.490	11.03^{***}
NIG	1810	0.628	5.966^{***}	0.007	0.099	1605	-1.020	-8.859^{***}	0.007	-0.145	1.648	11.43^{***}
PAK	2186	0.246	1.466	0.011	0.022	1365	-1.111	-7.402^{***}	0.010	-0.111	1.355	6.556^{***}
SRL	1929	0.431	3.284^{***}	0.008	0.054	1553	-1.023	-8.047^{***}	0.008	-0.128	1.454	8.609^{***}
FM	1875	0.497	3.203^{***}	0.009	0.052	1132	-0.718	-4.256^{***}	0.010	-0.011	1.216	9.123^{***}

Notes: '***', '**' and '*' denote 1%, 5% and 10% significance levels. The *t*-statistics are reported for each market. The first column lists all the 30 markets under scrutiny. The second column reports the number of buy signals (N_b). The third column reports the difference between the buy returns and the unconditional buy-and-hold (BH) returns. The fourth column reports the *t*-statistic of the difference of the buy returns from the BH returns. The fifth column reports the standard deviation of the difference of the buy returns from the BH returns. The sixth column reports the return-to-volatility (RV_b) ratios as the mean buy divided by the standard deviation. The seventh column reports the number of sell signal. The eighth column reports the different between the sell returns and the BH returns. The ninth column reports the test statistics of the difference of the sell return from the BH returns. The tenth column reports the standard deviation of the differences between the sell returns and BH returns. The eleventh column reports the return-to-volatility (RV_s) ratios as the mean sell divided by the standard deviation. The twelfth column reports the difference of the buy returns from the sell returns and their test-statistics are reported in the thirteenth column.

Table 1.8: Full Period – MACD Trading Rule

Mkts.	N_b	Mean Buy (10^{-3})	t-stat	SD_b	RV_b	N_s	Mean Sell (10^{-3})	t-stat	SD_s	RV_s	Buy-sell (10^{-3})	t-stat
Panel A: Developed Markets												
UK	1191	-0.122	-0.706	0.011	-0.011	871	0.025	0.179	0.009	0.000	-0.147	-1.014
GER	1330	-0.170	-0.791	0.014	-0.012	792	-0.274	-1.494	0.012	-0.023	0.104	0.598
FRA	1334	-0.172	-0.827	0.013	-0.013	857	-0.031	-0.181	0.011	-0.001	-0.140	-0.804
ITA	1148	0.152	0.708	0.014	0.011	948	-0.002	-0.009	0.012	-0.000	0.153	0.886
US	1270	-0.149	-0.830	0.012	-0.012	814	-0.115	-0.790	0.009	-0.013	-0.035	-0.239
CAN	1314	-0.142	-0.885	0.010	-0.014	728	-0.151	-1.066	0.009	-0.017	0.009	0.071
JAP	1096	0.037	0.176	0.011	0.000	912	-0.082	-0.452	0.014	-0.001	0.119	0.700
HK	1227	-0.086	-0.409	0.014	-0.000	867	-0.292	-1.629	0.012	-0.024	0.206	1.143
AUS	1355	-0.111	-0.797	0.009	-0.012	778	-0.169	-1.444	0.008	-0.021	0.059	0.508
EURO	1329	0.012	0.080	0.010	0.000	845	-0.089	-0.721	0.008	-0.011	0.101	0.844
DEV	1269	-0.097	-0.455	0.006	-0.016	875	-0.035	-0.195	0.010	-0.000	-0.062	-0.359
Panel B: Emerging Markets												
RUS	1289	0.065	0.164	0.026	0.000	806	-0.767	-1.919*	0.026	-0.029	0.830	3.182***
POL	1271	-0.104	-0.591	0.011	-0.001	818	-0.488	-2.902***	0.011	-0.044	0.284	2.617***
MEX	1374	-0.279	-1.465	0.012	-0.023	749	-0.568	-3.257***	0.011	-0.052	0.289	1.895*
BRZ	1253	-0.169	-0.678	0.016	-0.011	859	-0.455	-2.012**	0.015	-0.033	0.287	1.385
IND	1341	-0.205	-0.952	0.014	-0.015	749	-0.556	-2.850***	0.014	-0.040	0.351	2.036**
CHI	1094	0.157	0.755	0.013	0.012	972	-0.381	-1.929*	0.013	-0.029	0.537	3.031***
TUR	1263	-0.066	-0.214	0.020	-0.000	863	-0.737	-2.579***	0.018	-0.041	0.671	2.474**
EGY	1267	0.054	0.245	0.014	0.000	755	-0.915	-4.216***	0.014	-0.065	0.969	4.811***
SA	1492	-0.308	-1.865*	0.011	-0.028	660	-0.531	-3.512***	0.010	-0.053	0.224	1.591
EM	1345	0.042	0.244	0.011	0.000	846	-0.522	-3.603***	0.009	-0.058	0.563	3.887***
Panel C: Frontier Markets												
ARG	1295	-0.047	-0.168	0.019	-0.000	783	-0.956	-3.537***	0.017	-0.056	0.909	3.670***
JAM	1174	-0.011	-0.116	0.006	-0.000	835	-0.477	-4.567***	0.007	-0.068	0.466	5.589***
ROM	1293	-0.081	-0.356	0.015	-0.001	656	-0.911	-3.999***	0.015	-0.067	0.829	4.278***
UKR	1102	0.127	0.529	0.015	0.001	849	-1.202	-5.117***	0.015	-0.080	1.328	6.089***
KEN	1082	0.349	2.889***	0.008	0.044	854	-0.504	-4.392***	0.007	-0.072	0.853	8.094***
NIG	1079	0.172	1.391	0.008	0.022	796	-0.678	-5.179***	0.008	-0.085	0.849	7.327***
PAK	1440	-0.042	-0.225	0.012	-0.000	618	-1.004	-5.471***	0.012	-0.084	0.962	6.035***
SRL	1125	0.085	0.548	0.010	0.000	805	-0.805	-5.224***	0.010	-0.081	0.890	7.368***
FM	1169	0.281	1.855*	0.009	0.031	576	-0.579	-3.704***	0.009	-0.064	0.861	8.294***

Notes: '***', '**' and '*' denote 1%, 5% and 10% significance levels

Table 1.9: Great Moderation Period – AMA Trading Rule

	N_b	Mean Buy (10^{-3})	t-stat	SD_b	RV_b	N_s	Mean Sell (10^{-3})	t-stat	SD_s	RV_s	Buy-sell (10^{-3})	t-stat
UK	1067	-0.084	-0.420	0.009	-0.001	747	0.092	0.584	0.007	0.013	-0.175	-0.753
GER	1100	0.068	0.246	0.013	0.001	723	-0.272	-1.228	0.010	-0.027	0.340	1.049
FRA	1148	-0.109	-0.451	0.011	-0.001	706	0.047	0.238	0.009	0.001	-0.157	-0.546
ITA	1211	0.053	0.256	0.009	0.001	630	-0.155	-0.843	0.008	-0.019	0.208	0.808
US	1001	-0.159	-0.797	0.009	-0.018	819	0.038	0.251	0.007	0.001	-0.198	-0.861
CAN	1183	0.017	0.102	0.008	0.002	646	-0.361	-2.449**	0.007	-0.052	0.378	1.789*
JAP	933	-0.117	-0.502	0.010	-0.012	835	-0.062	-0.310	0.009	-0.001	-0.055	-0.196
HK	1009	-0.028	-0.126	0.010	-0.000	757	-0.289	-1.429	0.009	-0.032	0.262	0.961
AUS	1146	-0.183	-1.512	0.006	-0.031	684	-0.266	-2.400**	0.005	-0.053	0.083	0.548
EURO	1060	0.115	0.741	0.007	0.016	809	-0.236	-1.909*	0.007	-0.034	0.351	1.966**
DEV	1104	-0.075	-0.295	0.012	-0.001	740	-0.312	-0.158	0.009	-0.035	-0.044	-0.147
RUS	1139	-0.186	-0.322	0.026	-0.001	658	-1.513	-2.507**	0.028	-0.054	1.327	2.790***
POL	1123	0.051	0.267	0.009	0.001	722	-0.768	-3.508***	0.010	-0.077	0.819	3.050***
MEX	1225	-0.189	-0.791	0.011	-0.017	605	-0.803	-3.589***	0.010	-0.080	0.614	2.084**
BRZ	1076	-0.161	-0.538	0.014	-0.012	756	-0.639	-2.246**	0.013	-0.042	0.478	1.294
IND	1111	0.029	0.019	0.012	0.001	699	-0.717	-3.328***	0.010	-0.072	0.726	2.331**
CHI	882	0.126	0.559	0.010	0.013	881	-0.542	-2.380**	0.010	-0.054	0.667	2.266**
TUR	1047	-0.195	-0.422	0.021	-0.001	758	-1.081	-2.549**	0.019	-0.057	0.885	1.563
EGY	1005	0.239	0.940	0.013	0.019	813	-1.427	-5.067***	0.013	-0.109	1.666	4.682***
SA	1184	-0.084	-0.458	0.008	-0.011	620	-0.689	-3.820***	0.008	-0.086	0.605	2.547***
EM	1124	0.130	0.754	0.008	0.016	757	-0.803	-5.334***	0.007	-0.076	0.933	4.507***
ARG	953	-0.211	-0.583	0.017	-0.012	824	-0.611	-1.821*	0.015	-0.041	0.399	0.878
JAM	1045	0.013	0.115	0.005	0.000	664	-0.817	-5.801***	0.006	-0.136	0.829	5.021***
ROM	1130	-0.102	-0.391	0.012	-0.001	611	-1.372	-4.703***	0.013	-0.106	1.269	3.435***
UKR	924	-0.408	-1.495	0.012	-0.034	831	-1.242	-4.147***	0.014	-0.089	0.834	2.250**
KEN	747	0.625	3.959***	0.007	0.089	903	-0.919	-6.837***	0.006	-0.153	1.543	7.698***
NIG	904	0.219	1.704*	0.006	0.037	723	-1.201	-7.513***	0.007	-0.160	1.419	7.419***
PAK	1025	0.229	0.837	0.012	0.019	762	-1.473	-6.190***	0.011	-0.134	1.701	5.098***
SRL	970	0.301	1.409	0.010	0.030	762	-1.084	-5.095***	0.010	-0.108	1.384	4.971***
FM	766	0.204	0.812	0.009	0.023	359	-1.032	-4.063***	0.009	-0.115	1.236	6.142***

Notes: ‘***’, ‘**’ and ‘*’ denote 1%, 5% and 10% significance levels

Table 1.10: Great Moderation Period – MACD Trading Rule

Mkts	N_b	Mean Buy (10^{-3})	t-stat	SD_b	RV_b	N_s	Mean Sell (10^{-3})	t-stat	SD_s	RV_s	Buy-sell (10^{-3})	t-stat
UK	608	-0.175	-0.789	0.010	-0.018	429	0.156	0.828	0.009	0.017	-0.331	-1.812*
GER	667	-0.207	-0.665	0.014	-0.015	401	-0.261	-0.975	0.012	-0.022	0.054	0.216
FRA	720	-0.259	-0.954	0.012	-0.022	395	-0.109	-0.451	0.011	-0.001	-0.150	-0.668
ITA	662	-0.057	-0.238	0.011	-0.001	401	-0.191	-0.886	0.010	-0.019	0.134	0.678
US	597	-0.087	-0.389	0.010	-0.001	456	0.031	0.162	0.009	0.000	-0.118	-0.691
CAN	688	-0.169	-0.875	0.009	-0.019	364	-0.229	-1.245	0.008	-0.029	0.059	0.395
JAP	556	-0.007	-0.028	0.012	-0.001	462	-0.116	-0.482	0.011	-0.011	-0.116	-0.482
HK	652	-0.171	-0.683	0.011	-0.016	406	-0.394	-1.666*	0.011	-0.036	0.222	1.044
AUS	708	-0.215	-1.538	0.006	-0.036	354	-0.338	-2.611***	0.006	-0.036	0.123	1.063
EURO	653	0.014	0.082	0.008	0.000	445	-0.092	-0.611	0.007	-0.013	0.106	0.764
DEV	664	-0.120	-0.419	0.013	-0.001	419	-0.035	-0.141	0.011	-0.003	-0.085	-0.376
RUS	752	-0.512	-0.899	0.026	-0.019	301	-1.316	-2.404**	0.025	-0.053	0.804	2.227**
POL	716	-0.298	-1.261	0.011	-0.027	348	-0.762	-3.053***	0.011	-0.069	0.463	2.329***
MEX	750	-0.464	-1.678*	0.013	-0.036	304	-0.980	-3.689***	0.012	-0.082	0.517	2.392**
BRZ	689	-0.389	-1.145	0.016	-0.024	388	-0.876	-2.658***	0.015	-0.058	0.487	1.692*
IND	717	-0.225	-0.759	0.014	-0.016	361	-0.752	-2.738***	0.013	-0.058	0.527	2.146***
CHI	530	0.029	0.112	0.012	0.000	480	-0.466	-1.812*	0.012	-0.038	0.495	2.107**
TUR	635	-0.360	-0.698	0.024	-0.015	412	-0.951	-1.958*	0.022	-0.043	0.590	1.282
EGY	646	-0.068	-0.234	0.013	-0.001	368	-1.279	-3.949***	0.015	-0.085	1.211	4.183***
SA	766	-0.372	-1.760*	0.010	-0.037	322	-0.770	-3.740***	0.009	-0.086	0.398	2.118**
EM	747	-0.043	-0.225	0.009	-0.000	367	-0.799	-4.434***	0.008	-0.099	0.755	4.665***
ARG	653	0.028	0.069	0.018	0.000	381	-1.012	-2.501**	0.018	-0.056	1.039	2.917***
JAM	663	-0.114	-0.847	0.006	-0.019	298	-0.828	-5.173***	0.007	-0.118	0.714	5.728***
ROM	734	-0.461	-1.520	0.014	-0.033	247	-1.358	-3.819***	0.016	-0.085	0.897	3.347***
UKR	623	-0.639	-2.024	0.014	-0.046	361	-1.634	-4.881***	0.015	-0.109	0.995	3.334***
KEN	470	0.469	2.709***	0.008	-0.059	418	-0.569	-3.251***	0.008	-0.071	1.039	6.802***
NIG	597	-0.361	-2.471**	0.007	-0.052	277	-1.098	-5.865***	0.009	-0.122	0.737	4.856***
PAK	716	-0.229	-0.779	0.013	-0.012	347	-1.362	-4.589***	0.014	-0.097	1.133	4.305***
SRL	608	-0.087	-0.340	0.012	-0.001	366	-0.962	-3.698***	0.012	-0.081	0.874	4.609***
FM	488	-0.167	-0.692	0.009	-0.019	160	-1.098	-4.727***	0.008	-0.137	0.931	5.916***

Notes: ‘***’, ‘**’ and ‘*’ denote 1%, 5% and 10% significance levels

Table 1.11: Great Austerity Period – AMA Trading Rule

	N_b	Mean Buy (10^{-3})	t-stat	SD_b	RV_b	N_s	Mean Sell (10^{-3})	t-stat	SD_s	RV_s	Buy-sell (10^{-3})	t-stat
UK	1078	-0.078	-0.322	0.011	-0.001	776	0.088	0.534	0.008	0.011	-0.166	-0.609
GER	1093	-0.076	-0.281	0.012	-0.001	757	-0.254	-1.211	0.010	-0.025	0.178	0.585
FRA	1046	-0.052	-0.176	0.014	-0.000	817	0.119	0.624	0.009	0.013	-0.172	-0.524
ITA	981	0.341	1.038	0.015	0.023	866	0.153	0.702	0.010	0.015	0.188	0.517
US	1153	-0.067	-0.258	0.012	-0.006	680	-0.129	-0.765	0.008	-0.016	0.062	0.211
CAN	1148	0.010	0.044	0.011	0.000	685	-0.068	-0.403	0.008	-0.001	0.078	0.302
JAP	929	0.009	0.032	0.014	0.000	860	0.037	0.165	0.010	0.000	-0.027	-0.082
HK	966	0.107	0.345	0.014	0.001	830	-0.305	-1.354	0.010	-0.031	0.412	1.160
AUS	1050	0.143	0.637	0.010	0.014	820	-0.044	-0.291	0.007	-0.001	0.187	0.747
EURO	1152	0.196	0.879	0.010	0.019	712	-0.213	-1.334	0.007	-0.031	0.409	1.682*
DEV	1023	-0.079	-0.270	0.013	-0.001	830	-0.077	-0.399	0.009	-0.015	-0.002	-0.008
RUS	898	0.790	1.389	0.026	0.030	863	-0.360	-0.582	0.028	-0.001	1.115	2.327***
POL	1023	0.135	0.593	0.010	0.014	788	-0.226	-1.175	0.009	-0.025	0.361	1.311
MEX	1080	-0.011	-0.043	0.011	-0.000	735	-0.229	-1.203	0.009	-0.025	0.219	0.794
BRZ	921	0.152	0.449	0.015	0.010	893	-0.009	-0.037	0.011	-0.000	0.161	0.420
IND	1055	-0.064	-0.235	0.012	-0.001	749	-0.284	-1.271	0.010	-0.028	0.219	0.665
CHI	860	0.350	1.188	0.013	0.027	881	-0.423	-1.758*	0.011	-0.038	0.773	2.245**
TUR	1023	0.243	0.786	0.014	0.017	818	-0.526	-2.159**	0.011	-0.048	0.769	2.102**
EGY	994	0.781	2.495**	0.014	0.056	749	-0.887	-4.044***	0.010	-0.089	1.668	4.639***
SA	1211	-0.217	-0.971	0.010	-0.022	629	-0.131	-0.699	0.009	-0.015	-0.085	-0.319
EM	1050	0.351	1.353	0.012	0.029	812	-0.367	-1.866*	0.009	-0.041	0.718	2.467**
ARG	975	0.035	0.098	0.016	0.022	816	-0.834	-2.882**	0.013	-0.064	0.868	2.018**
JAM	940	0.127	1.091	0.005	0.025	927	-0.102	-0.922	0.005	-0.020	0.229	1.489
ROM	976	0.355	1.158	0.014	0.025	832	-0.336	-1.418	0.011	-0.031	0.691	1.956*
UKR	921	1.427	4.435***	0.014	0.102	903	-1.376	-4.957***	0.013	-0.091	2.803	7.122***
KEN	1070	0.719	5.182***	0.006	0.119	752	-0.718	-5.339**	0.006	-0.119	1.438	7.934***
NIG	906	1.038	6.227***	0.008	0.128	882	-0.839	-5.066**	0.008	-0.105	1.877	8.706***
PAK	1161	0.264	1.349	0.009	0.071	600	-0.746	-4.098***	0.008	-0.093	1.009	4.136***
SRL	959	0.560	3.683***	0.007	0.080	789	-0.965	-6.890***	0.006	-0.161	1.525	7.958***
FM	1109	0.671	3.403***	0.009	0.074	772	-0.532	-2.389**	0.010	-0.53	1.203	6.853***

Notes: '***',** and '*' denote 1%, 5% and 10% significance levels

Table 1.12: Great Austerity Period – MACD Trading Rule

	N_b	Mean Buy (10^{-3})	t-stat	SD_b	RV_b	N_s	Mean Sell (10^{-3})	t-stat	SD_s	RV_s	Buy-sell (10^{-3})	t-stat
UK	583	-0.069	-0.261	0.012	-0.001	442	-0.107	-0.536	0.009	0.012	0.037	0.167
GER	663	-0.133	-0.449	0.014	-0.001	391	-0.287	-1.144	0.011	-0.026	0.155	0.638
FRA	614	-0.084	-0.269	0.014	-0.001	462	0.046	0.183	0.011	0.000	-0.013	-0.130
ITA	547	0.260	1.017	0.016	0.016	486	0.187	0.655	0.013	0.014	0.173	0.608
US	673	-0.213	-0.749	0.012	-0.018	358	-0.261	-1.195	0.010	-0.026	0.048	0.207
CAN	626	-0.114	-0.447	0.012	-0.001	364	-0.072	-0.337	0.010	-0.001	-0.016	-0.073
JAP	540	0.082	0.247	0.015	0.001	450	-0.048	-0.177	0.012	-0.000	0.130	0.491
HK	575	-0.001	-0.003	0.015	-0.000	461	-0.192	-0.708	0.012	-0.016	0.190	0.653
AUS	647	-0.007	-0.028	0.011	-0.000	424	-0.001	-0.007	0.009	-0.000	-0.006	-0.028
EURO	676	0.009	0.039	0.011	0.000	400	-0.086	-0.439	0.009	-0.001	0.096	0.491
DEV	605	-0.074	-0.234	0.014	-0.001	456	-0.034	-0.135	0.012	-0.000	-0.039	-0.150
RUS	537	0.641	1.169	0.025	0.025	505	-0.216	-0.372	0.027	-0.001	0.857	2.272***
POL	555	0.090	0.345	0.012	0.001	470	-0.214	-0.949	0.010	-0.021	0.304	1.411
MEX	624	-0.094	-0.359	0.012	-0.001	445	-0.157	-0.694	0.010	-0.011	0.063	0.291
BRZ	564	0.052	0.143	0.017	0.000	471	-0.035	-0.113	0.014	-0.000	0.087	0.292
IND	624	-0.185	-0.592	0.014	-0.013	388	-0.361	-1.310	0.013	-0.028	0.176	0.726
CHI	564	0.283	0.881	0.015	0.019	492	-0.298	-0.987	0.014	-0.021	0.579	2.182**
TUR	628	0.278	0.667	0.016	0.017	451	-0.523	-1.736**	0.014	-0.037	0.751	2.619***
EGY	621	0.176	0.519	0.015	0.012	387	-0.551	-1.908*	0.013	-0.042	0.727	2.596***
SA	726	-0.244	-0.962	0.012	-0.020	338	-0.291	-1.318	0.010	-0.018	0.047	0.229
EM	598	0.127	0.444	0.013	0.001	479	-0.245	-1.081	0.010	-0.025	0.372	1.547
ARG	642	-0.121	-0.315	0.018	-0.001	402	-0.900	-2.509**	0.016	-0.056	0.779	2.263**
JAM	537	0.180	0.899	0.009	0.020	511	0.026	0.104	0.012	0.000	0.307	1.997**
ROM	559	0.298	0.878	0.015	0.019	409	-0.464	-1.630	0.013	-0.036	0.762	2.718***
UKR	479	0.891	2.473**	0.016	0.056	488	-0.769	-2.338**	0.015	-0.051	1.660	5.219***
KEN	612	0.228	1.357	0.008	0.029	436	-0.439	-2.957***	0.007	-0.063	0.667	4.596***
NIG	519	0.704	3.541***	0.009	0.070	482	-0.258	-1.415	0.008	-0.032	0.962	5.489***
PAK	724	0.634	0.527	0.015	0.042	271	-0.647	-2.996***	0.010	-0.065	0.791	4.396***
SRL	517	0.257	1.467	0.008	0.032	439	-0.649	-3.914***	0.008	-0.081	0.906	6.051***
FM	681	0.548	2.823***	0.009	0.061	193	-0.272	-1.309	0.009	-0.030	0.819	6.001***

Notes: '***', '**' and '*' denote 1%, 5% and 10% significance levels

1.5.4 The Profitability of Trading Rules Over time

We first illustrate the changed profitability over time by assuming that $100 is invested in each market at the beginning of the sample period. Figure 1.3 demonstrates the cumulative wealth of investing on the buy-and-hold (BH), AMA and MACD strategies. The plots of the cumulative wealth of the BH strategy is compared with the technical trading strategies. The graphs further depict the profitability of the technical trading strategies during the GM and GA periods. The three plots show similar trend behaviours though with different intensities. There have been swings in cumulative wealth with the occurrence of downswings in recessionary and crisis periods (2000 - 2002 dot-com bubble bust and 2007 – 2009 global financial crisis) and upswings in expansionary and boom periods (2003 – 2007 housing market bubble and 2009 - 2013 quantitative easing asset bubble).

For the UK stock market, the MACD strategy beats the BH and AMA strategies between 2002 and 2006. From 2008 to 2015, the AMA strategy has consistently beaten the BH and MACD strategies. This suggests that the MACD strategy is profitable during tranquil and booming years while AMA strategy is successful during increasingly volatile times. The cumulative wealth of BH strategy fluctuates across the full 16-year sample period and it reaches $100.12 while the AMA (MACD) strategy reaches the end-of-period wealth of $100.16 ($99.95). This result is similar in the Canadian market.

Similarly, AMA strategy ouperforms the BH and MACD strategies in most periods of GM and GA in France. The AMA and MACD strategies only beat the BH strategy in Italy between 2011 and 2015. In the US, the MACD strategy beats the BH and AMA strategies only during the GM period and technical trading strategies have been unprofitable throughout the GA period. This results contrast with Fang *et al.'s* (2014) finding that technical trading rule seldom outperforms the market. The MACD strategy effectively beats the BH and AMA strategies between 2003 and 2006 in the GM period and from 2010 to 2015 in the GA period for the Japanese market. This suggests that the MACD rule is a profitable strategy to use in this market. The MACD strategy consistently ouperforms the BH and AMA strategies in both GM and GA periods for MSCI developed markets.

Turning to the emerging and frontier equity markets, the AMA strategy beats the BH and MACD strategies in most GA period for Russian, Brazilian and Chinese markets. The MACD strategy outperforms the BH and AMA strategies from 2009 to 2015 in the diversified frontier markets (MSCI). The AMA strategy outperforms the BH and MACD strategies from 2003 to 2015 in the Pakistan market whereas for the Sri Lanka market the AMA strategy only beats the BH strategy between 2004 and 2008. The AMA strategy has consistently outperforms the BH and MACD strategies for the Nigerian market while the MACD strategy beats the BH and AMA strategies for the Kenyan market. This indicates that technical trading rules can exploit the potential profits due to the relative inefficiency of the Sub-Saharan African markets.

In contrast, technical trading strategies are clearly not profitable in half of the markets as they consistently lie below the BH strategy in cumulative wealth for developed markets of Germany, Hong Kong, Australia, Euro Area; emerging markets of Poland, Mexico, India, Turkey, Egypt, South Africa, MSCI emerging markets; and frontier markets of Argentina, Jamaica, Romania and Ukraine. This suggests overall that dynamic trading rule profitability exists in at least half of the markets, hence supporting the AMH paradigm.

Furthermore, we then examine the technical trading rules profitability on a risk-adjusted basis using the Jensen (1968) market model. Using a single-variable linear regression, we regress the excess return of a technical trading strategies on the excess return of the BH strategy as follows;

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_p\left(r_{m,t} - r_{f,t}\right) + \varepsilon_t \qquad (1.22)$$

where $r_{p,t}$ is the return on technical trading rules; $r_{f,t}$ represent the risk free rate[11] (that is, 3-month Treasury bill rate historical data);[12] α_p (alpha) captures the excess returns over what is expected such that value statistically greater than zero indicates an evidence of risk-adjusted profits and a value less than zero suggests that the trading rule is unable to forecast market return; β_p represents the systematic risk of the technical trading rules;[13] $r_{m,t}$ represents the BH returns; ε_t represents the residual term which captures idiosyncratic or non-systematic risks.

Table 1.13, Table 1.14 and Table 1.15 report the alphas and betas for the AMA and MACD strategies. Starting with the full period for the AMA strategy, 12 out of 30 markets generate positive significant alphas by employing the buy trading signals while 23 out of 30 markets produce negative significant alphas by employing the sell trading signals. For the MACD strategy, the buy trading signals generate positive significant alphas in 10 out of 30 markets, whereas negative significant alphas are generated in 23 out of 30 markets from the sell trading signals. The positive alphas are found only in emerging and frontier markets suggesting that technical trading strategies do produce superior returns on a risk-adjusted basis. However, based

[11] The risk free rate is free of interest rate risk due to short term maturities and reasonably safe in terms of default or credit risk.
[12] The 3-month Treasury bill rate for each country was obtained from Bloomberg and Federal Reserve Bank of St. Louis. Considering the period of study from 1999, the bond market of the emerging and frontier markets are gradually becoming more liquid, stable and developed, hence the use of the 3-month Treasury bill is a better proxy of risk free rate.
[13] The beta parameter captures economic factor such as business cycles, interest rates and other economic conditions that affect the overall market risk.

on the MACD buy-and-sell trading signals, negative significant alphas are generated for MSCI emerging, Brazilian and Jamaican markets, which suggests that for a given level of risk, investing on the MACD strategy is not as profitable as investing on the market. The AMA buy-and-sell signals are insignificant for all markets.

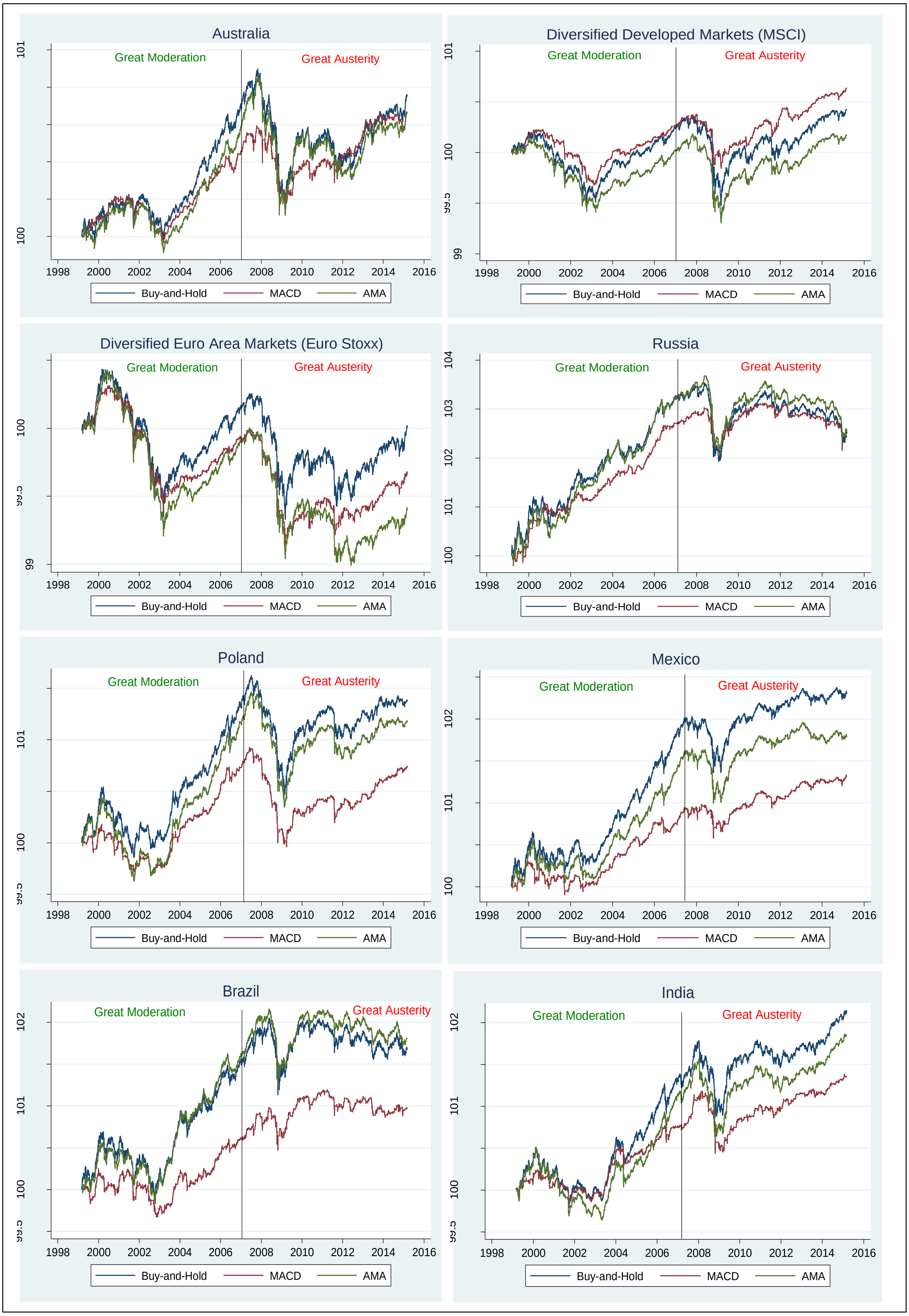
During the GM period, 10 out of 30 markets generate positive significant alphas for the AMA buy signals while 22 out of 30 markets generate negative significant alphas for the AMA sell signals. The MACD buy signals generate positive significant alphas in 7 out of 30 markets, whereas negative significant alphas are generated in 19 out of 30 markets for the MACD sell signals. The AMA and MACD buy-and-sell signals are found to generate negative significant alphas in 9 out of 30 markets, which suggests that technical trading strategies do not generate a superior risk-adjusted returns in a tranquil period.

During the GA period, 8 out of 30 markets generate positive significant alphas for the AMA buy trading signals whereas 15 out of 30 markets produce negative significant alphas for the AMA sell signals. The MACD buy trading signals generate 5 out of 30 markets whereas negative significant alphas are generated in 16 out of 30 markets for the MACD sell trading signals. The AMA buy-and-sell signals are found to generate positive significant alphas in Italy, Brazil and Pakistan suggesting risk-adjusted profits exist investing on this technical trading strategy. The negative significant alphas are generated in 6 out of 30 markets for the MACD buy-and-sell trading signals (Poland, Egypt, Jamaica, Romania, Ukraine and Kenya) which suggests that this technical trading strategy do not generate superior return on a risk-adjusted basis.

Most of the beta coefficients are positively significant and less than one, suggesting that the return on technical trading strategy is less volatile than the return on the BH strategy. Stock markets with high betas indicate increased systematic risk, whereas low betas suggest reduced systematic risk. In both the full, GM and GA periods, the beta coefficient for MACD buy signal is less than the AMA buy signal, suggesting increased sensitivity to systematic risk during stock market upturn, hence boosting investors' confidence to buy more stocks. In contrast, the beta coefficient for the AMA sell signal is greater than that of the MACD sell signal, indicating increased sensitivity to systematic risk during market downturn, leading to investor's stock sell-off.

In summary, the AMA buy-sell strategy outperforms the MACD and BH strategies on the basis of risk-adjusted profits in Italy, Brazil and Pakistan during the GA period. This suggests that we cannot rule out the hypothesis that traders gradually implemented technical trading rules in these markets. Nevertheless, the incorporation of transaction costs could reduce or eliminate technical rule profitability thereby casting further doubts on the efficiency of technical trading strategies in these markets. We further argue that financial market operators have increasingly exploited and diminished the returns to technical trading strategies over time for most markets. The diminution of profits depends on the speed with which the market learns about and exploit the strategies which is consistent with the AMH. Therefore, the structural changes that have occurred in many markets is increasing the speed of market price movements, thereby reducing technical trading rules profitability.


UK
Great Moderation
Great Austerity
Buy-and-Hold
MACD
AMA
Germany
France
Italy
US
Canada
Japan
Hong Kong
cbhhk
cmacdhk
cmahk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Buy-and-Hold MACD AMA
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Diversified Euro Area Markets (Euro Stoxx)
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Buy-and-Hold MACD AMA
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Buy-and-Hold MACD AMA
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India
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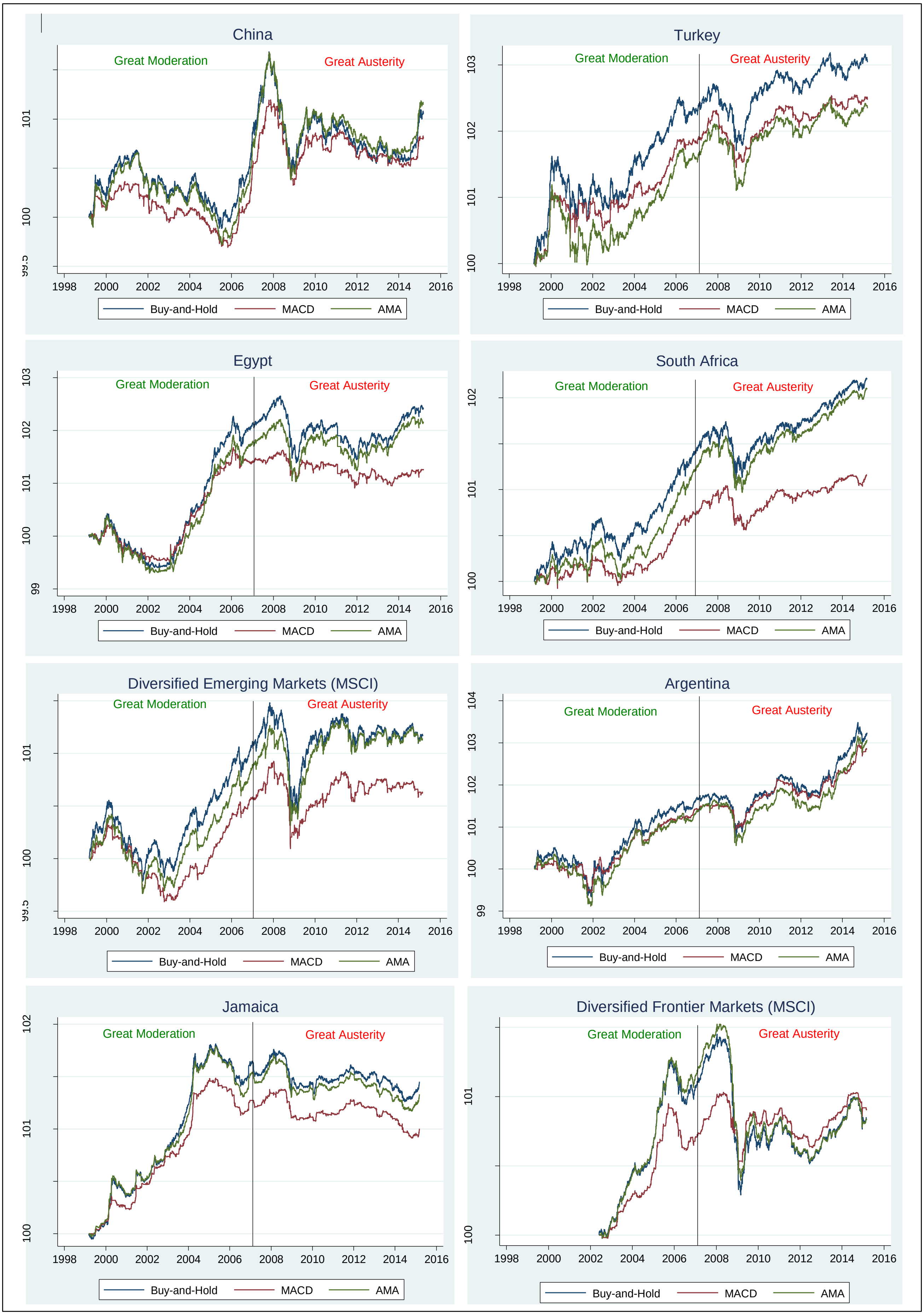
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Buy-and-Hold
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Diversified Emerging Markets (MSCI)
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Buy-and-Hold
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Buy-and-Hold
MACD
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Jamaica
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Buy-and-Hold
MACD
AMA
Diversified Frontier Markets (MSCI)
Great Moderation
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Buy-and-Hold
MACD
AMA

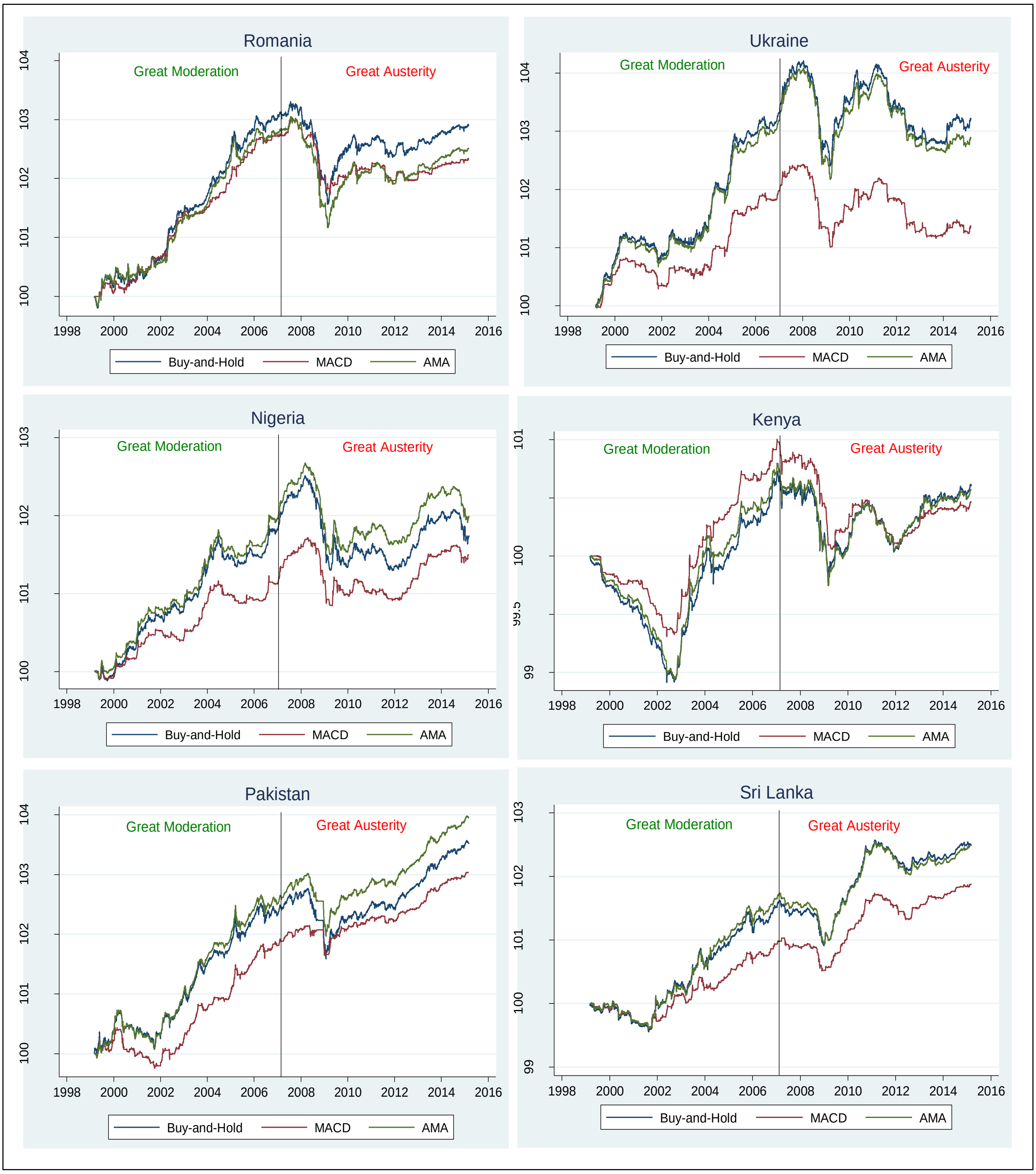


Figure 1.3: Cumulative Wealth of the Buy-and-Hold, MACD and AMA Strategies

Table 1.13: Risk-Adjusted Profits of AMA and MACD Trading Rules – Full Period

	AMA						***MACD***					
	Buy		Sell		Buy & sell		Buy		Sell		Buy & sell	
Market	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p
UK	-0.143*	0.290*	0.057	0.630*	0.029	0.919*	-0.197*	0.141*	-0.022	0.460*	-0.105	0.601*
	(0.085)	(0.017)	(0.090)	(0.199)	(0.050)	(0.010)	(0.065)	(0.010)	(0.093)	(0.025)	(0.091)	(0.021)
GER	0.083	0.318*	-0.209*	0.578*	-0.046	0.896*	-0.063	0.161*	-0.196*	0.389*	-0.179	0.549*
	(0.109)	(0.017)	(0.116)	(0.019)	(0.072)	(0.011)	(0.086)	(0.011)	(0.114)	(0.023)	(0.117)	(0.021)
FRA	-0.107	0.289*	0.070	0.630*	0.006	-0.024	-0.202*	0.167*	-0.525	0.421*	-0.199	-0.013
	(0.103)	(0.016)	(0.109)	(0.019)	(0.218)	(0.023)	(0.083)	(0.012)	(0.112)	(0.023)	(0.174)	(0.019)
ITA	0.052	0.298*	-0.079	0.624*	0.056	0.921*	-0.024	0.149*	-0.125	0.406*	-0.066	0.556*
	(0.106)	(0.016)	(0.112)	(0.018)	(0.062)	(0.009)	(0.083)	(0.011)	(0.114)	(0.023)	(0.115)	(0.020)
US	-0.080	0.275*	-0.030	0.656*	0.009	-0.069*	-0.109*	0.128*	-0.089	0.432*	-0.097	-0.046*
	(0.086)	(0.018)	(0.092)	(0.020)	(0.186)	(0.026)	(0.065)	(0.010)	(0.096)	(0.028)	(0.145)	(0.021)
CAN	0.091	0.324*	-0.168	0.591*	0.014	0.915*	-0.046	0.159*	-0.076	0.346*	-0.031	0.505*
	(0.082)	(0.020)	(0.087)	(0.025)	(0.049)	(0.019)	(0.064)	(0.012)	(0.084)	(0.027)	(0.088)	(0.027)
JAP	-0.018	0.311*	0.009	0.575*	0.034	0.543*	0.081	0.158*	-0.049	0.385*	-0.005	0.886*
	(0.107)	(0.018)	(0.115)	(0.023)	(0.115)	(0.023)	(0.085)	(0.012)	(0.113)	(0.027)	(0.074)	(0.019)
HK	-0.027	0.339*	-0.339*	0.579*	-0.060	0.917*	-0.167*	0.188*	-0.351*	0.409*	-0.060	0.918*
	(0.111)	(0.020)	(0.115)	(0.023)	(0.064)	(0.011)	(0.091)	(0.015)	(0.115)	(0.029)	(0.064)	(0.011)
AUS	0.005	0.919*	-0.156*	0.617*	-0.022	0.303*	-0.113*	0.170*	-0.171*	0.407*	-0.102	0.577*
	(0.040)	(0.011)	(0.074)	(0.019)	(0.070)	(0.017)	(0.057)	(0.012)	(0.075)	(0.025)	(0.075)	(0.022)
EURO	-0.137	0.287*	-0.084	0.641*	-0.211	-0.028	-0.167*	0.641*	-0.083	0.414*	-0.211	-0.024
	(0.104)	(0.016)	(0.018)	(0.018)	(0.222)	(0.023)	(0.082)	(0.018)	(0.114)	(0.023)	(0.173)	(0.019)
DEV	0.157*	0.283*	-0.224*	0.603*	0.032	0.886*	0.013	0.153*	-0.224*	0.603*	0.024	0.558*
	(0.072)	(0.017)	(0.078)	(0.023)	(0.051)	(0.017)	(0.058)	(0.012)	(0.078)	(0.023)	(0.072)	(0.017)
RUS	0.532*	0.033*	-0.714*	0.064*	-0.002	0.916*	0.301*	0.005	-0.536*	0.035*	0.023	0.529*
	(0.207)	(0.012)	(0.272)	(0.023)	(0.099)	(0.013)	(0.169)	(0.008)	(0.198)	(0.019)	(0.179)	(0.026)
POL	0.139	0.442*	-0.454*	0.475*	0.007	0.059*	-0.042	0.233*	-0.431*	0.301*	-0.180	0.039*
	(0.099)	(0.019)	(0.101)	(0.019)	(0.192)	(0.019)	(0.085)	(0.015)	(0.093)	(0.021)	(0.147)	(0.015)
MEX	0.067	0.382*	-0.387*	0.521*	-0.036	0.904*	-0.062	0.196*	-0.386*	0.323*	-0.164	0.519*
	(0.103)	(0.019)	(0.106)	(0.021)	(0.904)	(0.012)	(0.084)	(0.013)	(0.099)	(0.023)	(0.106)	(0.022)
BRZ	-0.088	0.343[a]	-0.379*	0.566*	0.061	0.909*	-0.269*	0.207*	-0.539*	0.343*	-0.281*	0.549*
	(0.133)	(0.016)	(0.138)	(0.019)	(0.080)	(0.010)	(0.113)	(0.013)	(0.133)	(0.022)	(0.139)	(0.019)
IND	0.148	0.349*	-0.393*	0.578*	0.251	0.048*	0.001	0.188**	-0.387*	0.333*	-0.001	0.035
	(0.113)	(0.027)	(0.118)	(0.025)	(0.232)	(0.026)	(0.093)	(0.014)	(0.114)	(0.026)	(0.174)	(0.022)
CHI	0.318*	0.391*	-0.419*	0.516*	0.139	0.391*	0.256*	0.241**	-0.291*	0.314*	0.160	-0.008
	(0.116)	(0.021)	(0.119)	(0.022)	(0.227)	(0.021)	(0.102)	(0.018)	(0.110)	(0.021)	(0.178)	(0.160)
TUR	0.357*	0.385*	-0.546*	0.523*	-0.000	0.908*	0.346*	0.237*	-0.385*	0.349*	0.149	0.586*
	(0.171)	(0.022)	(0.177)	(0.024)	(0.104)	(0.016)	(0.149)	(0019)	(0.169)	(0.027)	(0.175)	(0.022)
EGY	0.642*	0.405*	-1.053*	0.535*	0.124	0.152*	0.214*	0.279*	-0.763*	0.314*	-0.081	0.109*
	(0.128)	(0.027)	(0.131)	(0.131)	(0.251)	(0.032)	(0.117)	(0.027)	(0.123)	(0.023)	(0.199)	(0.031)
SA	-0.013	0.404*	-0.298*	0.514*	0.192	0.034	-0.128*	0.219*	-0.380*	0.344*	-0.083	0.016
	(0.092)	(0.018)	(0.094)	(0.020)	(0.179)	(0.022)	(0.077)	(0.013)	(0.089)	(0.022)	(0.141)	(0.019)
EM	0.228*	0.322*	-0.593*	0.571*	-0.068	0.893*	0.026	0.172*	-0.533*	0.416*	-0.228*	0.588*
	(0.088)	(0.019)	(0.094)	(0.024)	(0.058)	(0.023)	(0.072)	(0.013)	(0.093)	(0.028)	(0.093)	(0.023)
ARG	0.131	0.391*	-0.555*	0.536*	-0.006	0.927*	0.214	0.274*	-0.707*	0.308*	-0.075	0.582*
	(0.159)	(0.021)	(0.163)	(0.022)	(0.085)	(0.010)	(0.144)	(0.020)	(0.151)	(0.021)	(0.161)	(0.020)
JAM	0.012	0.530*	-0.532*	0.409*	-0.158	0.052*	-0.095*	0.316*	-0.576*	0.197*	-0.256*	0.056 *
	(0.059)	(0.031)	(0.058)	(0.030)	(0.113)	(0.028)	(0.055)	(0.028)	(0.046)	(0.021)	(0.084)	(0.025)
ROM	0.182	0.425*	-0.805*	0.501*	0.056	0.087*	-0.011	0.267*	-0.840*	0.266*	-0.205	0.042*
	(0.132)	(0.034)	(0.133)	(0.033)	(0.255)	(0.029)	(0.118)	(0.033)	(0.118)	(0.028)	(0.194)	(0.025)
UKR	0.534*	0.442*	-1.430*	0.459*	0.046	0.469*	0.313*	0.278*	-1.185*	0.598*	-0.286	0.453*
	(0.261)	(0.233)	(0.259)	(0.223)	(0.326)	(0.219)	(0.141)	(0.025)	(0.185)	(0.167)	(0.282)	(0.228)
KEN	0.579*	0.429*	-0.894*	0.531*	-0.009	0.960*	0.144	0.582*	-0.614*	0.325*	-0.079	0.577*
	(0.069)	(0.043)	(0.069)	(0.045)	(0.027)	(0.008)	(0.186)	(0.174)	(0.671)	(0.049)	(0.069)	(0.046)
NIG	0.629*	0.512*	-1.019*	0.417*	0.023	0.929*	0.173*	0.336*	-0.676*	0.254*	-0.090	0.590*
	(0.075)	(0.021)	(0.074)	(0.020)	(0.039)	(0.008)	(0.072)	(0.020)	(0.066)	(0.018)	(0.075)	(0.020)
PAK	0.556*	0.398*	-0.862*	0.519*	0.024	0.917*	0.337*	0.264*	-0.634*	0.281*	0.033	0.544*
	(0.106)	(0.019)	(0.109)	(0.020)	(0.006)	(0.089)	(0.096)	(0.018)	(0.099)	(0.020)	(0.109)	(0.019)
SRL	0.539*	0.447*	-0.922*	0.479*	0.017	0.926*	0.236*	0.232*	-0.656*	0.240*	-0.021	0.471*
	(0.087)	(0.047)	(0.088)	(0.046)	(0.049)	(0.023)	(0.074)	(0.026)	(0.077)	(0.032)	(0.089)	(0.044)
FM	0.389*	0.046*	-0.823*	0.084*	0.020	0.914*	0.171*	0.029*	-0.687*	0.053*	-0.099	0.552*
	(0.078)	(0.009)	(0.018)	(0.031)	(0.039)	(0.018)	(0.065)	(0.009)	(0.081)	(0.020)	(0.069)	(0.038)

Notes: '*' denotes 10% significance level. Standard errors are in parenthesis.

Table 1.14: Risk-Adjusted Profits of AMA and MACD Trading Rules – GM Period

	AMA						***MACD***					
	Buy		Sell		Buy & sell		Buy		Sell		Buy & sell	
Market	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p
UK	-0.206*	0.328*	0.016	0.586*	-0.014	0.914*	-0.326*	0.167*	0.047	0.399*	-0.105	0.565*
	(0.114)	(0.023)	(0.119)	(0.025)	(0.068)	(0.012)	(0.090)	(0.016)	(0.119)	(0.029)	(0.120)	(0.026)
GER	0.082	0.333*	-0.263	0.576*	-0.053	0.909*	-0.190	0.162*	-0.249	0.380*	-0.310*	0.543*
	(0.160)	(0.023)	(0.168)	(0.025)	(0.098)	(0.013)	(0.126)	(0015)	(0.165)	(0.028)	(0.169)	(0.026)
FRA	-0.103	0.348*	0.052	0.564*	0.069	-0.008	-0.250*	0.192*	-0.102	0.365*	-0.233	0.024
	(0.144)	(0.023)	(0.149)	(0.026)	(0.288)	(0.029)	(0.119)	(0.016)	(0.145)	(0.029)	(0.225)	(0.024)
ITA	0.008	0.394*	-0.189	0.531*	-0.071	0.925*	-0.118	0.191*	-0.239*	0.352*	-0.246*	0.543*
	(0.131)	(0.025)	(0.133)	(0.027)	(0.071)	(0.012)	(0.105)	(0.018)	(0.127)	(0.031)	(0.133)	(0.027)
US	-0.216*	0.305*	0.005	0.608*	-0.169	-0.018	-0.156*	0.144*	-0.021	0.359*	-0.097	-0.009
	(0.111)	(0.022)	(0.117)	(0.024)	(0.229)	(0.028)	(0.084)	(0.013)	(0.116)	(0.026)	(0.170)	(0.019)
CAN	0.136	0.408	-0.268*	0.539*	0.006	0.947*	-0.009	0.203*	-0.085	0.280	0.039	0.483[a]
	(0.108)	(0.028)	(0.109)	(0.030)	(0.049)	(0.009)	(0.088)	(0.019)	(0.098)	(0.026)	(0.109)	(0.031)
JAP	-0.076	0.372*	-0.032	0.539*	-0,104	0.911	0.045	0.193*	-0.072	0.335*	-0.023	0.527*
	(0.142)	(0.023)	(0.147)	(0.024)	(0.084)	(0.012)	(0.116)	(0.017)	(0.139)	(0.024)	(0.147)	(0.024)
HK	-0.030	0.408*	-0.292*	0.499*	-0.010	0.906*	-0.175	0.234*	-0.396*	0.319*	-0.259*	0.553*
	(0.141)	(0.027)	(0.143)	(0.028)	(0.084)	(0.013)	(0.121)	(0.022)	(0.133)	(0.031)	(0.142)	(0.027)
AUS	-0.096	0.411*	-0.193*	0.507*	-0.086*	0.917*	-0.099	0.215*	-0.238*	0.326*	-0.134*	0.540*
	(0.078)	(0.026)	(0.079)	(0.028)	(0.043)	(0.011)	(0.065)	(0.017)	(0.076)	(0.033)	(0.079)	(0.027)
EURO	-0.113	0.327*	-0.054	0.597[a]	-0.108	-0.026	-0.168	0.156*	-0.070	0.372*	-0.151	0.002
	(0.146)	(0.023)	(0.153)	(0.025)	(0.299)	(0.029)	(0.113)	(0.014)	(0.151)	(0.028)	(0.226)	(0.024)
DEV	0.102	0.327*	-0.244*	0.569*	-0.009	0.897*	-0.001	0.180*	-0.104	0.362*	0.027	0.542*
	(0.089)	(0.021)	(0.093)	(0.021)	(0.057)	(0.014)	(0.073)	(0.015)	(0.009)	(0.026)	(0.094)	(0.025)
RUS	0.840*	0.041*	-0.475	0.030	-0.084	0.898*	0.544*	0.014	-0.254	0.008	0.214	0.515*
	(0.312)	(0.016)	(0.351)	(0.023)	(0.146)	(0.023)	(0.279)	(0.015)	(0.225)	(0.014)	(0.256)	(0.031)
POL	0.198	0.520*	-0.583*	0.393*	0.222	0.023	-0.083	0.292*	-0.052*	0.211*	-0.109	0.017
	(0.141)	(0.026)	(0.138)	(0.026)	(0.269)	(0.026)	(0.128)	(0.022)	(0.117)	(0.024)	().199)	(0.019)
MEX	0.097	0.413*	-0.055*	0.483*	-0.074	0.896*	-0.081	0.212*	-0.625*	0.270*	-0.326*	0.482*
	(0.153)	(0.025)	(0.156)	(0.026)	(0.094)	(0.018)	(0.127)	(0.017)	(0.139)	(0.026)	(0.156)	(0.026)
BRZ	-0.075	0.888[a]	-0.609*	0.473*	-0.128	0.415*	-0.347*	0.247*	-0.836*	0.292*	-0.520*	0.539*
	(0.124)	(0.016)	(0.196)	(0.023)	(0.193)	(0.021)	(0.169)	(0.018)	(0.178)	(0.023)	(0.196)	(0.022)
IND	0.330	0.329[a]	-0.636*	0.589*	0.205	0.088	0.145	0.209*	-0.583*	0.367*	-0.058*	0.065
	(0.161)	(0.027)	(0.169)	(0.032)	(0.221)	(0.054)	(0.139)	(0.020)	(0.168)	(0.042)	(0.265)	(0.051)
CHI	0.311*	0.462[a]	-0.354*	0.454*	0.356	0.012	0.276*	0.281*	-0.226	0.302*	0.349	-0.008
	(0.152)	(0.033)	(0.152)	(0.032)	(0.296)	(0.028)	(0.138)	(0.032)	(0.139)	(0.031)	(0.236)	(0.023)
TUR	0.349	0.403*	-0.621*	0.497*	-0.056	0.899*	0.321	0.254*	-0.347	0.339*	0.189	0.593*
	(0.292)	(0.029)	(0.298)	(0.032)	(0.185)	(0.022)	(0.256)	(0.026)	(0.285)	(0.035)	(0.293)	(0.029)
EGY	0.571*	0.521*	-1.022*	0.416*	0.041	0.153*	0.355*	0.390*	-0.745*	0.229*	0.278	0.127*
	(0.182)	(0.036)	(0.180)	(0.033)	(0.349)	(0.055)	(0.175)	(0.042)	(0.157)	(0.025)	(0.279)	(0.053)
SA	0.114	0.457*	-0.495*	0.468*	0.266	0.061*	-0.107	0.272*	-0.517*	0.307*	-0.080	0.031
	(0.124)	(0.027)	(0.124)	(0.029)	(0.240)	(0.032)	(0.111)	(0.022)	(0.116)	(0.031)	(0.191)	(0.028)
EM	0.232*	0.377*	-0.725*	0.525*	-0.149*	0.902*	0.082	0.231*	-0.688*	0.321*	-0.261*	0.522*
	(0.106)	(0.022)	(0.109)	(0.024)	(0.065)	(0.013)	(0.093)	(0.017)	(0.103)	(0.027)	(0.109)	(0.024)
ARG	0.131	0.391*	-0.427*	0.501*	-0.005	0.917*	0.287	0.293*	-0.744*	0.273*	-0.038	0.565*
	(0.158)	(0.021)	(0.163)	(0.031)	(0131)	(0.016)	(0.213)	(0.032)	(0.212)	(0.026)	(0.235)	(0.029)
JAM	0.084	0.596*	-0.698*	0.328*	0.081	0.175	-0.006	0.393*	-0.675*	0.133*	-0.052	0.149*
	(0.083)	(0.040)	(0.079)	(0.038)	(0.162)	(0.039)	(0.082)	(0.041)	(0.059)	(0.024)	(0.121)	(0.037)
ROM	0.143	0.528*	-1.067*	0.415*	0.437	0.106*	-0.132	0.369*	-0.905*	0.128*	0.145	0.054*
	(0.189)	(0.054)	(0.187)	(0.055)	(0.369)	(0.036)	(0.189)	(0.056)	(0.131)	(0.027)	(0.265)	(0.027)
UKR	0.807*	0.078*	-1.913*	-0.154*	-0.522	0.232*	0.378*	0.238*	-1.198*	0.363*	-0.646*	0.157*
	(0.259)	(0.018)	(0.285)	(0.032)	(0.398)	(0.037)	(0.179)	(0.028)	(0.195)	(0.039)	(0.309)	(0.032)
KEN	0.602*	0.408*	-0.935*	0.568*	-0.022	0.974*	0.442*	0.289*	-0.598*	0.276*	0.156	0.563*
	(0.100)	(0.070)	(0.101)	(0.073)	(0.033)	(0.008)	(0.093)	(0.052)	(0.093)	(0.086)	(0.102)	(0.079)
NIG	0.407*	0.584*	-0.907*	0.353*	0.013	0.936*	-0.119	0.467*	-0.697*	0.117*	-0.303*	0.582*
	(0.098)	(0.033)	(0.095)	(0.033)	(0.495)	(0.009)	(0.101)	(0.034)	(0.066)	(0.019)	(0.098)	(0.033)
PAK	0.785*	0.387*	-1.049*	0.534*	-0.009	0.920*	0.411*	0.295*	-0.705*	0.276*	-0.038	0.571*
	(0.173)	(0.026)	(0.176)	(0.027)	(0.095)	(0.011)	(0.162)	(0.025)	(0.159)	(0.026)	(0.176)	(0.026)
SRL	0.494*	0.459*	-0.892*	0.464*	0.016	0.923*	0.189	0.227*	-0.676*	0.201*	-0.074	0.428*
	(0.144)	(0.068)	(0.147)	(0.066)	(0.085)	(0.033)	(0.121)	(0.036)	(0.122)	(0.043)	(0.146)	(0.061)
FM	0.711*	0.038*	-0.504*	-0.002	0.111	0.911*	0.348*	0.021	-0.576*	0.009	-0.140	0.557*
	(0.147)	(0.016)	(0.136)	(0.028)	(0.069)	(0.028)	(0.124)	(0.015)	(0.099)	(0.016)	(0.109)	(0.045)

Notes: ‘*’ denotes 10% significance level. Standard errors are in parenthesis.

Table 1.15: Risk-Adjusted Profits of AMA and MACD Trading Rules – GA Period

	AMA						*MACD*					
	Buy		Sell		Buy & sell		Buy		Sell		Buy & sell	
Markets	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p	α_p **(10^{-3})**	β_p
UK	-0.073	0.262*	0.090	0.663*	0.072	0.924*	-0.063	0.121*	-0.103	0.506*	-0.112	0.626*
	(0.125)	(0.023)	(0.134)	(0.028)	(0.075)	(0.016)	(0.092)	(0.013)	(0.141)	(0.036)	(0.137)	(0.031)
GER	0.088	0.301*	-0.155*	0.580*	-0.036	0.882*	0.064	0.159*	-0.146*	0.398*	-0.050	0.557*
	(0.149)	(0.025)	(0.159)	(0.031)	(0.105)	(0.019)	(0.119)	(0.016)	(0.158)	(0.037)	(0.161)	(0.032)
FRA	-0.115	0.243*	0.093	0.682*	-0.058	-0.036	-0.156	0.149*	0.000	0.465*	-0.169	-0.043
	(0.146)	(0.021)	(0.158)	(0.025)	(0.326)	(0.034)	(0.121)	(0.016)	(0.164)	(0.034)	(0.266)	(0.030)
ITA	0.087	0.249*	0.041	0.670*	0.183*	0.919*	0.065	0.129	-0.005	0.433*	0.115	0.562*
	(0.164)	(0.020)	(0.178)	(0.024)	(0.101)	(0.012)	(0.013)	(0.014)	(0.189)	(0.030)	(0.188)	(0.027)
US	0.616	0.257*	-0.075	0.687*	0.198	-0.101*	-0.059	0.118*	-0.171	0.478*	-0.089	-0.069*
	(0.132)	(0.025)	(0.141)	(0.028)	(0.294)	(0.038)	(0.098)	(0.014)	(0.152)	(0.039)	(0.234)	(0.032)
CAN	0.029	0.272*	-0.058	0.623*	0.022	0.895*	-0.091	0.132*	-0.056	0.387*	-0.097	0.519*
	(0.122)	(0.026)	(0.133)	(0.036)	(0.085)	(0.031)	(0.093)	(0.015)	(0.134)	(0.041)	(0.137)	(0.039)
JAP	0.038	0.269*	0.053	0.599*	0.093	0.869*	0.116	0.134*	-0.257	0.419*	0.092	0.554*
	(0.159)	(0.024)	(0.175)	(0.035)	(0.121)	(0.032)	(0.122)	(0.017)	(0.177)	(0.040)	(0.178)	(0.035)
HK	-0.031	0.298*	-0.37b	0.627*	-0.109	0.925*	-0.165	0.161*	-0.296	0.463*	-0.161	0.624*
	(0.169)	(0.027)	(0.179)	(0.031)	(0.098)	(0.015)	(0.136)	(0.018)	(0.184)	(0.039)	(0.179)	(0.032)
AUS	0.029	0.263*	-0.097	0.658*	0.096	0.921*	-0.137	0.154*	-0.088	0.437*	-0.062	0.591*
	().115)	(0.019)	(0.123)	(0.024)	(0.069)	(0.014)	(0.094)	(0.015)	(0.129)	(0.032)	(0.128)	(0.028)
EURO	-0.161	0.253*	-0.112	0.678*	-0.315	-0.029	-0.167	0.145*	-0.095	0.448*	-0.272	-0.045
	(0.148)	(0.021)	(0.159)	(0.024)	(0.327)	(0.034)	(0.119)	(0.015)	(0.169)	(0.033)	(0.261)	(0.029)
DEV	0.212*	0.259*	-0.204	0.621*	0.073	0.881*	0.029	0.138*	-0.074	0.428*	0.020	0.566*
	(0.114)	(0.024)	(0.126)	(0.032)	(0.084)	(0.025)	(0.089)	(0,016)	(0.128)	(0.038)	(0.129)	(0.035)
RUS	0.209	0.023	-0.898*	0.096*	0.109	0.933*	0.044	-0.004	-0.775*	0.060	-0.143	0.544*
	(0.269)	(0.018)	(0.413)	(0.039)	(0.128)	(0.018)	(0.190)	(0.007)	(0.329)	(0.036)	(0.254)	(0.042)
POL	-0.193	0.093*	-0.242	0.061*	0.044	-0.004	0.046	0.367*	-0.289*	0.553*	-0.775*	0.060
	(0.274)	(0.028)	(0.214)	(0.024)	(0.190)	(0.007)	(0.138)	(0.026)	(0.142)	(0.027)	(0.329)	(0.037)
MEX	0.024	0.347*	-0.206	0.565*	0.006	0.913*	-0.051	0.176*	-0.123	0.386*	0.013	0.562*
	(0.137)	(0.029)	(0.143)	(0.032)	(0.082)	(0.014)	(0.109)	(0.019)	(0.140)	(0.038)	(0.143)	(0.032)
BRZ	-0.073	0.274*	-0.115	0.657*	0.205*	0.931*	-0.207	0.168*	-0.224	0.392*	-0.037	0.559*
	(0.177)	(0.022)	(0.189)	(0.026)	(0.099)	(0.012)	(0.149)	(0.017)	(0.195)	(0.037)	(0.197)	(0.033)
IND	0.027	0.363*	-0.223	0.572*	0.258	0.039	-0.065	0.162*	-0.267	0.341*	0.024	0.015
	(0.164)	(0.042)	(0.169)	(0.041)	(0.333)	(0.031)	(0.126)	(0.015)	(0.163)	(0.038)	(0.242)	(0.021)
CHI	0.296*	0.341*	-0.459*	0.561*	-0.082	-0.001	0.219	0.212*	-0.351*	0.323*	-0.029	-0.009
	(0.172)	(0.026)	(0.179)	(0.028)	(0.345)	(0.029)	(0.148)	(0.019)	(0.169)	(0.029)	(0.266)	(0.023)
TUR	0.355*	0.338*	-0.457*	0.589*	0.059	0.927*	0.363*	0.196*	-0.418*	0.373*	0.107	0.569*
	(0.179)	(0.024)	(0.187)	(0.026)	(0.099)	(0.011)	(0.151)	(0.018)	(0.184)	(0.031)	(0.189)	(0.029)
EGY	0.604*	0.291*	-0.974*	0.651*	-0.163	0.152*	-0.031	0.171*	-0.701	0.398*	-0.457*	0.090*
	(0.168)	(0.026)	(0.176)	(0.029)	(0.354)	(0.035)	(0.140)	(0.019)	(0.179)	(0.037)	(0.276)	(0.033)
SA	-0.156	0.363*	-0.089	0.549*	0.110	0.012	-0.166	0.177*	-0.232*	0.374*	-0.089	0.004
	(0.135)	(0.025)	(0.139)	(0.028)	(0.267)	(0.031)	(0.107)	(0.015)	(0.136)	(0.031)	(0.208)	(0.026)
EM	0.209	0.295*	-0.449*	0.594*	0.012	0.889*	-0.046	0.142*	-0.353*	0.463*	-0.147	0.606*
	(0.140)	(0.027)	(0.151)	(0.033)	(0.095)	(0.023)	(0.108)	(0.016)	(0.153)	(0.038)	(0.151)	(0.032)
ARG	0.259	0.363*	-0.685*	0.576*	-0.009	0.939*	0.142	0.252*	-0.671*	0.349*	-0.112	0.601*
	(0.216)	(0.027)	(0.222)	(0.029)	(0.108)	(0.012)	(0.194)	(0.023)	(0.215)	(0.033)	(0.219)	(0.028)
JAM	-0.104	0.450*	-0.309*	-0.105	-0.481*	-0.098*	-0.237*	0.222*	-0.432*	0.275*	-0.525*	-0.058*
	(0.082)	(0.048)	(0.082)	(0.082)	(0.154)	(0.032)	(0.066)	(0.031)	(0.070)	(0.036)	(0.116)	(0.025)
ROM	0.131	0.316*	-0.469*	0.593*	-0.342	0.067	0.023	0.162*	-0.656*	0.412*	-0.565*	0.029
	(0.171)	(0.033)	(0.181)	(0.035)	(0.349)	(0.046)	(0.137)	(0.019)	(0.180)	(0.039)	(0.277)	(0.043)
UKR	0.807*	0.078*	-1.913*	0.155*	-0.522	0.232*	0.378*	0.238*	-1.198*	0.363*	-0.647*	0.157*
	(0.258)	(0.018)	(0.285)	(0.032)	(0.398)	(0.037)	(0.179)	(0.028)	(0.195)	(0.039)	(0.309)	(0.032)
KEN	0.564*	0.456*	-0.864*	0.488*	-0.000	0.944*	0.003	0.211*	-0.615*	0.383*	-0.312*	0.594*
	(0.096)	(0.039)	(0.096)	(0.038)	(0.042)	(0.014)	(0.079)	(0.027)	(0.093)	(0.039)	(0.096)	(0.039)
NIG	0.795*	0.459*	-1.079*	0.465*	0.028	0.924*	0.362*	0.239*	-0.546*	0.359*	0.129	0.598*
	(0.113)	(0.026)	(0.112)	(0.025)	(0.062)	(0.012)	(0.099)	(0.021)	(0.109)	(0.025)	(0.111)	(0.025)
PAK	0.055	0.912	-0.684*	0.495*	0.335*	0.417*	0.242*	0.205*	-0.559*	0.291*	0.086	0.496*
	(0.073)	(0.014)	(0,128)	(0.029)	(0.126)	(0.028)	(0.103)	(0.019)	(0.117)	(0.030)	(0.129)	(0.029)
SRL	0.581*	0.423*	-0.947*	0.511*	0.019	0.932*	0.284*	0.242*	-0.625*	0.321*	0.045	0.562*
	(0.098)	(0.032)	(0.099)	(0.032)	(0.051)	(0.012)	(0.085)	(0.025)	(0.094)	(0.031)	(0.099)	(0.033)
FM	0.201*	0.048*	-0.966*	0.122*	-0.033	0.915*	0.069	0.031*	-0.730*	0.072*	-0.076	0.551*
	(0.089)	(0.011)	(0.148)	(0.042)	(0.049)	(0.023)	(0.073)	(0.012)	(0.113)	(0.029)	(0.084)	(0.051)

Notes: '*' denotes 10% significance level. Standard errors are in parenthesis.

1.5.5 *Drivers of Technical Rule Profitability*

In this section, we employ panel data framework to examine the potential factors driving the cross-sectional and time-variation of technical rule profitability. The panels consist of 3072 observations (16 national markets for the cross-sectional data and 192 time series data).[14] Similar to Ülkü and Prodan (2013) and Neely *et al.* (2009), the technical trading rule returns are used as dependent variable. We perform the estimation for each technical trading rule separately by considering the following potential indicators; stock returns volatility, stock volume volatility, stock index futures volatility, volatility of macroeconomic fundamentals (interest rates, foreign exchange rates, industrial output and inflation), and historical episodes (housing bubbles, global financial crisis, Eurozone debt crisis, 11th September 2001 terrorist attack/Iraq invasion). We use the second moment - volatility as a proxy for new information hitting the market, hence leads to higher return predictability that can be exploited using technical analysis. This analysis will shed light on the impact of macro-finance factors and changing market conditions on the technical trading rule profitability.

The results of panel regression using random effects estimator are reported in Table 1.16. This estimator is efficient and allows the inclusion of time-invariant explanatory variables (e.g. the historical crisis periods), unlike the fixed effects estimator. The choice of the random effects estimator was based on the Hausman test specification. For the full period analysis, the stock return volatility has no significant effect on AMA rule profitability, whereas stock return volatility significantly increases MACD rule profitability. This suggests that increasing market volatility may be due to the intensity of new information arrivals thereby retarding the speedy incorporation of this news in market prices. Hence, rising trends will give opportunity for the profitability of technical trading rules. In the GM period, the stock return volatility increases MACD rule profitability but plays no part on AMA rule profitability. This is consistent with the findings that returns to technical rules increase with market volatility (see Boyd and Brorsen, 1992; Ülkü and Prodan, 2013).

In both GM and GA periods, the volatilities of stock volume and index futures have no influence on technical rule profitability, suggesting market depth and market liquidity play no active role in trading strategies. We may argue that as a result of the sample used in our panel regression which consist mostly of developed markets, the high level of stock market development improves the informational efficiency of the market.

[14] Due to availability of data and employing a balanced panel, we consider the national stock markets in UK, Germany, France, Italy, US, Canada, Japan, Australia, Euro Area, Russia, Poland, Mexico, Brazil, China, Turkey and South Africa.

For macroeconomic fundamentals, the inflation and exchange rate volatility positively influence the AMA rule profitability at 10% significant level. This is consistent with the existing evidence showing that exchange rate volatility is a potential driver of technical rule profitability (see Neely *et al.* 2009; Owen and Palmer, 2012). In the GM period, inflation volatility significantly increases AMA rule profitability with an estimated value of 0.032. In the GA period, the volatilities of interest rate and exchange rate are positively associated with AMA rule profitability. This suggests that when the macroeconomic fundamental volatility is high in crisis periods, AMA rule performs better because it accommodates changing economic condition. Conversely, macroeconomic/financial factors are not drivers of the MACD rule profitability in both periods. This implies that the MACD rule is insensitive to fundamental volatility, hence no linkage between profitability and macroeconomic variables.

For historical episodes, the crisis periods (dot-com bubble bust, global financial crisis, Eurozone debt crisis and September 11 attack/Afghanistan invasion) are associated with decline in technical trading rule profitability. In other words, the crisis periods lead to the decline in the profitability of the AMA and MACD rules. We argue that the decline in technical rule profitability due to negative shocks that hit the markets may be due to high level of uncertainty further aggravated by behavioural biases (for example, loss aversion, underreaction, overreaction, herding, momentum effect etc.) peculiar to portfolio investment decisions.

In summary, unlike the MACD rule, the AMA rule profitability is associated with macroeconomic factors and strongly related with changing market conditions. It is important to note that the AMA rule has the capacity to react automatically to changing market conditions in trending and ranging markets. The connection between changing market and economic fundamental, and technical trading profitability is consistent with the AMH.

Table 1.16: Panel Regression Results

	AMA			MACD		
Variables	**Full**	**GM**	**GA**	**Full**	**GM**	**GA**
Return volatility	0.083 (0.060)	0.119 (0.085)	-0.055 (0.082)	0.159*** (0.053)	0.233*** (0.068)	0.084 (0.062)
Inflation volatility	0.026* (0.015)	0.032* (0.019)	0.004 (0.027)	0.019 (0.014)	0.020 (0.015)	-0.018 (0.021)
Output volatility	-0.005 (0.038)	-0.001 (0.007)	-0.006 (0.004)	-0.005 (0.003)	-0.002 (0.005)	-0.005 (0.004)
Interest rate volatility	0.000 (0.000)	-0.001 (0.000)	0.001** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Exchange rate volatility	0.007* (0.004)	0.002 (0.006)	0.012** (0.005)	-0.004 (0.004)	-0.002 (0.005)	0.004 (0.003)
Volume volatility	-0.000 (0.000)	0.000 (0.000)	-0.001 (0.001)	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.000)
Stock futures volatility	-0.002 (0.001)	0.000 (0.003)	-0.000 (0.000)	-0.001 (0.000)	-0.002 (0.002)	-0.000 (0.000)
Dot-com bust	-0.001*** (0.000)	-0.001*** (0.000)		-0.001*** (0.000)	-0.001*** (0.000)	
Housing bubble	0.000 (0.000)	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)	
Global financial crisis	-0.001*** (0.000)		-0.001*** (0.000)	-0.001*** (0.000)		-0.001*** (0.000)
Eurozone debt crisis	-0.001*** (0.000)		-0.001*** (0.000)	-0.000*** (0.000)		-0.000** (0.000)
Sept 11 attack & Afghanistan Invasion	-0.002*** (0.000)	-0.002*** (0.001)		-0.003*** (0.000)	-0.003*** (0.000)	
Constant	0.000*** (0.000)	0.000 (0.000)	0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.001* (0.000)
R – squared	0.329	0.448	0.027	0.365	0.0646	0.039

Notes: '***', '**' and '*' denotes 1%, 5% and 10% significance levels. For the full period, we use the random effects estimator for the analysis based on the Hausman specification test. Cross-sectional data has 16 countries and time series data of 192 observations, yielding a total of 3072.

1.6 Conclusions

This chapter investigates the return predictability and technical trading rule profitability of developed, emerging and frontier equity markets over the period 1999 - 2015. We partitioned the full sample into periods of 'Great Moderation (GM)' and 'Great Austerity (GA)' for the purpose of comparative analysis.

First and foremost, we use Automatic Portmanteau test and Wild bootstrapped automatic variance ratio test to explain absolute and relative return predictability. The evidence shows that the degree of market efficiency varies over time in an oscillatory manner, especially in emerging and frontier markets, which is consistent with the adaptive market hypothesis (AMH). During the GA period for instance, return predictability declines in 60% of the markets, though it increases in most frontier markets. We argue that the improvement in market efficiency, notably in the developed markets suggests increased liquidity and well-functioning financial system typical of mature markets, whereas the deterioration in market efficiency, particularly in the frontier markets indicates increased market frictions common to immature markets. For instance, the most predictable markets are the frontier markets of Kenya and Nigeria while the least predictable markets are the developed markets of Japan and Canada. The market inefficiencies during period of crises are linked to market anomalies such as market crashes and panics. These market anomalies are sources of inefficiencies according to AMH, suggesting that profit opportunities may exist in the markets under consideration.

Furthermore, the predictive ability and profitability of the AMA and MACD trading rules may provide investors with crucial information on tactical asset allocation. The results that AMA and MACD trading rules exploit substantial information from past to predict future stock price changes is supported for few emerging markets and most frontier markets. For the developed markets, technical rules have no predictive power in Western European countries including the UK. The MACD and AMA rules provide generally consistent results though AMA rule outperforms the MACD rule. Based on the AMA buy-sell rule, we find that risk-adjusted profits exist in the markets located in Italy, Brazil and Pakistan during the GA period. Nevertheless, the excess profits that can be earned are economically small even before transaction costs are accounted for. Overall, both in cumulative wealth and risk-adjusted profits, technical trading rules do outperform the buy-and-hold strategies in some of the markets.

According to Lo (2004), "investment strategies will wax and wane, performing well in certain environments and perform poorly in other environments." This is consistent with our findings that the performance of technical rule profitability in the GM period exceeds the GA period. This further justifies that the market is adaptive such that the dynamic nature of the financial markets will engender investors' reaction to the non-stable relationship between risk and returns. However, as investors learn and adapt, the predictive power of technical trading rules tend to diminish over time, which is compatible with the AMH. The existing literature has attributed the dwindling profitability of technical rules to include, declining transactions costs and increasing liquidity in many markets arising from the use of advanced technology, enhanced information transmission underpinned by derivative trading, improvement in information processing by markets, pervasiveness of sophisticated institutional investors, better economic predictions (see Park and Irwin, 2007; Urquhart *et al.*, 2015).

Unlike the MACD rule, macroeconomic volatility adds to AMA rule profitability while period of political and economic crises (dot-com bust, Eurozone debt crisis, global financial crisis and September 11 attack/Afghanistan invasion) leads to a decline in technical rule profitability. This suggests that technical rule profitability is determined by macroeconomic fundamentals and changing market conditions which is line with AMH.

In conclusion, financial market operators should take into account both fundamental and non-fundamental impacts on stock prices movements in the assessment of the profitability of their investment decisions. Given the evidence that market anomalies and frictions are major sources of market inefficiencies, astute investors may systematically exploit profits using technical analysis nonetheless. The possibility of exploiting profit opportunities in these markets suggests that diversifying into these markets will yield potential benefits for investors in developed markets. It is as well important for policymakers to understand the market disruptions and uncertainties caused by shocks, crashes and bubbles, and should therefore be proactive in systematic intervention that will maintain overall financial stability.

Chapter 2. Stock Market Integration between UK and US: Evidence from 8-Decade-Long Data

2.1 Introduction

The financial markets among countries are increasingly becoming integrated and the process of integration is changing market dynamics in the areas of hedging, speculation and arbitrage strategies. On the one hand, deep financial market integration is evident in increased cross-border investments, improved capital allocation efficiency, risk diversification possibilities, higher resilient market liquidity, reduced likelihood of asymmetric shocks and improvement of global financial development (see, Umutlu *et al*., 2010; Yu *et al*., 2010). On the other hand, increasing financial market integration may also intensify the risk of cross-border financial contagion and financial stability risk (see, Beine *et al*., 2010; Buttner and Hayo, 2011). These risks may also limit the autonomy of macroeconomic policy adjustments and regulatory reforms of independent economies, which means there can be no tremendous divergence between policy in one country and the rest of the world. The underlying reason is not far-fetched in relating the growing convergence in policy responses to financial and economic shocks across countries in the globe. Whether financial market integration strengthens economic and financial development on the one hand, or conceals the risk of cross-border financial contagion on the other hand, it has important implications on portfolio management, macroeconomic policy framework and financial market stability.

Over the past three decades, the existing literature has investigated stock market integration from the dimensions of return behaviour, spillover effect and dynamic correlation. In the first place, the mechanisms of shock and volatility spillovers are underpinned by the transmission effects of domestic and international news affecting the global stock markets. This means that the pricing of domestic assets in an integrated markets can be influenced by international factors. Similarly, the series of shocks and unexpected changes in price movement may generate higher persistent volatilities in the financial markets. The importance attached to the second moment (i.e. volatility) than the first moment (i.e. mean) in the flow of information is stressed by Ross (1989). In this respect, the impact of independent shocks on the volatility of asset prices can be captured by the volatility impulse response function proposed by Hafner and Herwatz (2006).

A number of studies on volatility spillovers have used variants of GARCH model and inferences have been drawn on the dynamic of stock market integration. For instance, shocks originating in one financial market may potentially spill over to other markets more quickly, particularly when the markets are highly integrated. In a similar vein, it is expected that shocks become larger during crisis periods and their impacts across markets will be probably different when compared to stable periods. The return and volatility spillovers between financial markets have been documented in Hamao *et al.* (1990), Susmel and Engle (1994), Koutmos and Booth (1995), Martins and Poon (2001), Kim *et al*. (2005), Caporale *et al.* (2006), Panapoulou and Pantelidis (2009), Singh *et al.* (2010), Diebold and Yilmaz (2012), Olson *et al.* (2014).

Furthermore, increasing correlation between stock markets suggests higher co-movement and greater stock market integration (see for example, Kim *et al.* 2005; Wang and Moore, 2008). A number of scholars have found co-movements to be more time-varying and stronger in highly volatile periods (see, Longin and Solnik, 1995; Ramchand and Susmel, 1998; Ang and Bekaert, 2002; Aslanidis *et al*., 2010). Additionally, excessive increases in cross-country correlation of financial assets during crisis period relative to tranquil period have been interpreted as evidence of '*financial contagion*' (see, King and Wadhwani, 1990; Longin and Solnik, 1995; Forbes and Rigobon, 2002; Kallberg *et al.*, 2005; Chiang *et al*. 2007; Baur, 2012). According to Edward's (2000, p. 897) definition, "contagion occurs when the extent and magnitude of the international transmission of shocks exceed what was expected ex-ante." A practical illustration of '*contagion effect*' in recent times is evident in the transmission of 2007/2008 US subprime mortgage market crisis to other financial markets in the globe (see Longstaff, 2010; Kenourgious *et al.*, 2011; Bekaert *et al.*, 2014).[15] Given the transmission of shocks that cannot be explained by economic fundamentals, thus leading to excessive rise in stock market correlation, we may possibly consider the impact of key historical episodes in explaining some forms of contagion effects. Accordingly, the significant increase in cross-market correlation between two stock markets during tranquil and turbulent times would have crucial implications for portfolio allocation, asset pricing and public policy intervention.

The second strand of literature has shown that integration of international equity markets is inseparable from the underlying economic fundamentals and financial factors as well as the arrival of news on specific political and economic episodes (see, Fratzscher, 2002; Kim *et al.*, 2005; Kizys and Pierdziorch, 2006; Ehrmann, 2011; Syllignakis and Kouretas, 2011; Casalin and Dia, 2015). In general, the direction of stock market indices is used to gauge the health of the economy, which might comprise data on the Gross Domestic Product (GDP), Consumer

[15] Since the Great Depression of 1929 to 1932, the financial crisis of 2007 to 2009 is plausibly the first major crisis of an unprecedented global scale.

Price Index (CPI), interest rates, foreign exchange rates, employment indicators, balance of payments, government fiscal and monetary policy.[16] This is why in a period of economic expansion (contraction), we experience stock market growth (decline). It is therefore important to understand the relationship between these macroeconomic indicators and stock market integration.

In this chapter, we investigate the dynamics of integration between the United Kingdom (UK) and United States (US) stock markets for a period of eight decades starting from 1935. The dynamic integration between the two oldest stock market indices namely, the FT30 and Dow30, is critically important because of the rapid changes in political, economic, financial and technological environments with tremendous implications for financial market operators and policymakers. The cities of London and New York have remained the global financial centres over many decades, hence generalisation and inferences can be made for the universe of other developed markets.

In further analysis, we partition the full sample into six subsamples such as: The Interwar/Second World War (period 1: 1 July 1935 – 2 September 1945); The Bretton Woods System of fixed exchange rate regime (period 2: 3 September 1945 – 15 August 1971); The Pre-1979 UK Exchange controls (period 3: 16 August 1971 – 23 October 1979); The Post-1979 UK Exchange controls (period 4: 24 October 1979 – 30 June 1990); The Pre-European Monetary Union (period 5: 1 July 1990 – 31 December 1998) and the Post-European Monetary Union (period 6: 1 January 1999 – 30 June 2015).[17] This study will further enhance the understanding of both long- and short-term dynamics of stock market integration and yield a more detailed picture as to how the evolving international financial architecture underscores the changing sensitivity of financial markets to macroeconomic news and innovations. Unlike our well-defined subsamples, existing literature used different sub-periods in understanding the dynamics of financial integration (see Longin and Solnik, 1995; Ammer and Mei, 1996; Goetzmann *et al.,* 2005; Kim *et al.* 2005; Aslanidis *et al.,* 2010).

This chapter aims to shed light on the dynamics of financial integration and identify the determinants of stock market integration for the period of eight decades. To achieve this, the important research questions that would be answered through empirical analysis include:

[16] The stock market index is popularly used by investors as a barometer for gauging the economic performance of a nation and could therefore serve as a good proxy for measuring financial integration.
[17] The splitting of the sub-periods is not based on endogenous breaks but on structural changes in the political and economic systems of UK and US.

1. What is the nature of short- and long-run relationships between UK and US stock markets?
2. To what extent does shock and volatility spillover effects occur between the two markets?
3. What is the impact of historical observed shocks on conditional volatility based on the impulse response function of the markets?
4. Has the degree of stock market integration intensified over time and are there jumps in correlation levels from stable to crisis periods?
5. Can the degree of stock market integration be explained by macroeconomic fundamentals, stock market characteristics and market contagion?

This study is motivated by the benefit of a long data series which will deepen the understanding of investors, policymakers and researchers on the information transmission and cross-market dynamics in a rapidly changing financial markets. This study will help the market participants to understand the underlying factors driving the stock market integration process over time. It will also assist the policymakers to understand the determinants of stock market integration, thus have the capacity to contain threat to financial stability that may arise from investors' irrational exuberance.

Our study differ from previous studies and offer contributions to the relevant literature in many ways;

1. Kim *et al.* (2005) use the ARMA-EGARCH model to investigate the spill over effects between US and EMU over the period spanning from 1989 to 2003. We extend the sample period and use the VECM and asymmetric BEKK GARCH model to investigate the interdependence and interaction of UK and US stock markets in terms of return, shock and volatility transmission from 1935 to 2015. This model takes into account volatility clustering, speed of market information and information asymmetries. To our knowledge, this is the first study that will apply this model to comprehensively investigate if the direction and intensity of return and volatility dynamics between US and UK stock markets are altered in an evolving global financial system.
2. Panopoulou and Pantelidis (2009) use the BEKK model to investigate the interdependence and volatility impulse response of US and G7 countries from 1985 to 2004. We use the asymmetric BEKK model to evaluate the dynamic adjustment of volatilities in the US and UK stock markets to four historical shocks, namely; the 1987 stock market crash, the 11th September 2001 terrorist attacks, the 2003 Iraq invasion and

the 2008 global financial crisis. To our knowledge, apart from 1987 stock market crash, the impact of these historical innovations on volatilities of UK and US stock markets have not been investigated.

3. Aslanidis *et al.* (2010) use the STCC GARCH model to examine the co-movements between US and UK stock markets from 1980 to 2006. We extend by analysing the stock market integration between UK and US stock markets for the full sample and 6 subsamples over a period of 80 years using time-varying conditional correlation derived from asymmetric BEKK model. We further measure market contagion by excessive increase in volatilities and cross-market correlations in the period following a major crisis.
4. Kim *et al.* (2005) use the seemingly unrelated regression model to investigate the drivers of stock market integration between US and EMU. We extend by using the recently developed mixed data sampling (MIDAS) regression model to explore the drivers of stock market integration for the full sample and subsamples.

Our empirical results which addresses the gaps in the existing literature suggest the following;

(1) that long-run relationships exist between the UK and US stock markets for the full sample and subsamples, indicating stable long-run behaviour. This suggests that the presence of stock market cointegration and interdependence will foster international arbitrage among investors. We conclude therefore that the long-run relationship would have been driven partly by the impact of volatility spillover effects, market contagion, financial liberalisation and globalisation.

(2) that bidirectional return spillovers and causality exist between the UK and US markets for the full sample and most subsamples. However, the US market plays a dominant role in price discovery over the entire period, implying US financial hegemony in international financial markets. We attribute this result mainly to the activity of market participants in eliminating arbitrage opportunities thereby leading to rapid price adjustments that will reflect its fundamental value even when unexpected shocks hit the financial system.

(3) that the volatilities of the two markets are strongly interconnected as the shock and asymmetric volatility spillovers are bidirectional. The strong financial linkage between the two markets, particularly in post-EMU period suggests that growing degree of market integration, cross-border market contagion and financial globalisation play important role in the transmission mechanism. We argue that the movement towards

regional integration (e.g. EMU) will further strengthens the integration of the global economy.

(4) that the impact of historical episodes on volatilities (19^{th} October 1987 stock market crash, 11^{th} September 2001 attack and 15^{th} September 2008 collapse of Lehman Brothers Holdings) is stronger in the UK than the US stock market. This suggests that US as a 'global centre' plays a significant role in the transmission of shocks to the UK and rest of the world.

(5) that the UK and US markets are moderately correlated during stable periods but severe shocks (e.g. 1972/1973 oil shock, October 1987 market crash, 1997/1998 Asian and Russian crisis, and 2007/2009 Global financial crisis) to one market (US) lead to significant increase in stock market integration, suggesting some forms of market contagion.

(6) that stock market integration between UK and US has increased significantly from the interwar/WW2 period to the post-EMU period. The increasing integration is attributed to macroeconomic convergence, economic deregulation, financial liberalisation and globalisation

(7) finally, stock market integration has been driven by a number of major macroeconomic fundamentals (industrial output, inflation, interest rate and exchange rate), financial factors (oil and gold), stock market characteristics (stock return volatility and change in index composition) and major international episodes which have characterised the recent political economic history of the two economies.

The remainder of the chapter is structured as follows. Session 2.2 reviews the literature on stock market integration. Session 2.3 sets out the methodologies used to quantify cointegration relationships, spillover effects, impulse response functions as well as the important determinants of stock market integration. Session 2.4 describes the data-set. Section 2.5 sets out the empirical results and discusses some implications while session 2.6 concludes the chapter.

2.2 Literature Review

The literature on stock market integration has continued to generate interesting evidence amongst scholars. Many findings on financial integration have been linked further to volatility spillovers, portfolio management and market contagion. However, literature is scant on examining the asymmetric spillover mechanism, volatility impulse response and critical determinants of stock market integration in a rapidly changing global economy for a period of eight decades between the two major global stock markets (US and UK).

The chapter begins in section 2.2.1 with a brief discussion about the history of stock markets, with emphasis on the brief historical development of the oldest stock market indices in the US and UK. In section 2.2.2, we describe the evolution of international financial architecture by partitioning the 80-year long data into 6 subsamples in line with fundamental structural changes that have influenced financial market integration. Section 2.2.3 reviews the impact of macroeconomic and financial factors on the integration of stock markets. Finally, the existing empirical evidence on cointegration, spill-over effects and dynamics of financial market integration is our focus in section 2.2.4.

2.2.1 *History of Stock Markets – Dow30 and FT30 Indices*

The history of the stock markets started with the birth of Amsterdam stock exchange in 1611. Further development in the financial market led to the creation of the Austrian Bourse in 1771, which substantially traded in government bonds initially but later added equity and structured products. The exchange in the UK was launched with the establishment of the London Stock Exchange (LSE) in 1801. Securities trading in the US officially started with the setting up of New York Stock Exchange (NYSE) in 1817. Consequently, the international financial markets have experienced monumental development in the last four decades especially after the collapse of the Bretton Woods system. This brought about widespread financial liberalisation and globalisation in the developed countries from 1970s and developing countries from 1990s. Amongst the oldest stock markets, the US and UK financial markets have gained prominence leading to London and New York being designated as the top financial capitals of the world. Their stock market indices have been used by international investors as a barometer for gauging the country’s economic performance and could therefore serve as a good proxy for measuring financial integration.

To start with, the Dow Jones Industrial Average (DJIA) in US was launched by Charles Dow in 1896 and the index is simply computed based on the average stock prices of twelve large and diverse companies that were traded on the NYSE. Over the years, the Dow expanded to thirty US blue chip companies in October 1928 and now serves as an important measure of US economic performance for investors all over the world. The selection of stocks to be added to the index is not guided by quantitative rules but rather based on the company that exhibit excellent reputation, sustained growth, stock's attraction to a large number of investors and wide range sector representation (DJIA, 2013).

Since 1928, the DJIA (we prefer to use Dow30 in this study) is calculated as a scaled average by summing the prices of all thirty stocks and divide by the Dow divisor. A divisor was introduced to adjust for the effect of stock splits, stock distributions and stock substitutions (DJIA, 2013). The formula is given as;

$$\text{Dow30} = \frac{\Sigma p}{d}$$

where *p* are the prices of the constituent stocks and *d* is the Dow Divisor. As at September 2013, the divisor is 0.1557. The performance of the Dow30 has been influenced by corporate reports, macroeconomic news, political events (wars, terrorism etc.), natural disasters and other shocks. In the 128-year history, the components of the Dow30 have changed 51 times. Meanwhile, in the 80-year historical sample used in this chapter, the constituents have only changed 19 times.

Similar to Dow30 was the launching of the FT30 on 1st July 1935, and the index is based on the share price of thirty British Blue chip companies. The companies that make up the FT30 are being replaced for reasons of merger or failure. The index reflects the performance of the UK economy being the oldest continuous index. The index price is derived by the geometric average equal weighting for the thirty constituents. The selections of the constituents are based on the following; the constituent reflects the breadth of the UK economy; the shares are diversely and actively traded by investors; the company commands a leading height in its field and should be UK-based or have UK origin (FT30's history, 2006). From the outset, the constituents have been shifting from one industry dominance (e.g. textiles, coal in the 1950s) to another (e.g. telecommunication, financial services in the 1990s) reflecting the dynamic nature of the economy.

The index is calculated by an *adjustment based method* using the price movements since the previous day's closing index;

$$T_{Ind} = Y_{Ind} * 30\sqrt{\frac{tod_1}{yes_1} * \frac{tod_2}{yes_2} * \dots * \frac{tod_{30}}{yes_{30}}}$$

where T_{Ind} is the index today; Y_{Ind} is the index yesterday; $tod_1, tod_2, .., tod_{30},$ is the current share price of each of the 30 constituents; $yes_{1,}\ yes_2, \dots yes_{30}$ is yesterday's closing price of each constituent. Since 1935, the constituents have changed 56 times and this makes the index relatively unstable when compared to Dow30.

In summary, the FT30 and Dow30 indices both contain 30 blue chip companies of monumental national importance. Even though the FT30 has been superseded by the FTSE100 since 1984, both indices have significant similarities critical for the empirical analysis of their long- and short-run relationships. We will further examine if the change in constituents of these indices are drivers of stock market integration in subsequent sessions.

2.2.2 *Evolution of International Financial Architecture*

The UK and US financial markets have continued to maintain leading roles in financial liberalisation and development since the last eight decades. However, the relationships between their stock markets are presumably not stable over time perhaps due to changing market conditions. Hence, informing the need to partition the full sample into six subsamples based on structural changes that have shaped the political, economic and financial systems of the world. The subsamples are instrumental to our understanding of the long- and short-term dynamics of the evolution of stock market integration. The subsamples are explained below under the following headings; Interwar/Second World War, fixed exchange rate era of Bretton Woods System, pre-1979 UK exchange controls, post-1979 UK exchange controls, pre-EMU and post-EMU establishments.

A. Period of Interwar/Second World War (July 1, 1935 – September 2, 1945)

The worldwide severe economic crisis from 1929 to 1932, popularly referred to as the 'Great Depression' recorded series of stock market crashes, banking crisis, corporate bankruptcies, prolonged economic recessions and lower standard of living. After sequence of government interventions and reforms, economic recovery began but was later dampened by intermittent wars among foreign powers.

Figure 2.1 shows the plot of UK and US stock prices from 1st September 1935 to 2nd September 1945. The graph demonstrates the financial crisis/economic recession that occurred in 1937-

1938 period, leading to the decline in stock price of UK/US from its peak in March 1937 until its trough in March 1938 by 49.07%/28.56%. In reaction to the economic downturn, government interventions particularly in the US led to economic recovery. Consequently, the full-scale World War II began when Germany invaded Poland on 1st September 1939, leading to the declaration of war on Germany by France, UK and independent British Commonwealth countries. The US officially joined the Second World War in December 1941 after been attacked by Japan. This period was characterised by monumental global economic devastation and financial market instability. Typically, stock prices for UK and US plummeted to their historic lows from their peaks when they officially joined the war by 36.09% and 17.42%, respectively. This suggests that global political instability can lead to stock market crash and may persist if not contained with fiscal and monetary stimuli.

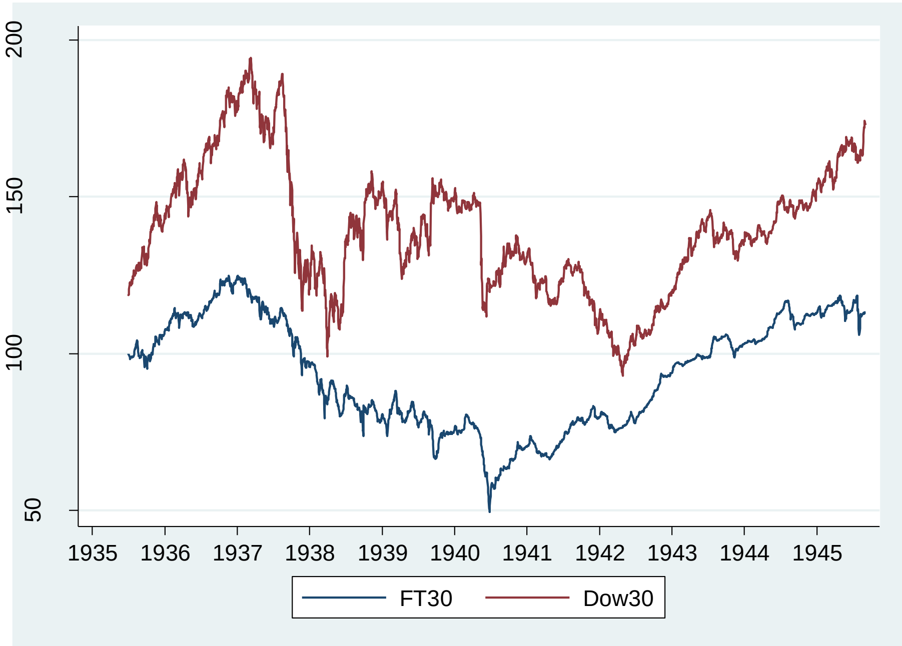


Figure 2.1: FT30 and Dow30 Indices in Interwar/Second World War Period

B. The Period of Bretton Woods System (3 September 1945 – 15 August 1971)

The years following the Second World War culminated in the establishment of the Bretton Woods System. The aim is to foster effective international monetary system so that unexpected currency depreciation and extreme fluctuations in exchange rates can be halted. The agreement signed by participating countries became operational in October 1945 and climaxed in the formation of the International Monetary Fund (IMF) and International Bank for Reconstruction and Development (IBRD), now known as World Bank. One of the key rules of the agreement is for each country to undertake a monetary policy that pegs its currency to the US dollar, hence creating a system of fixed exchange rates regime among countries. The objective is to facilitate international trade and improve capital flows. In order to achieve this goal, trade liberalisation strategy was further promoted through the General Agreement on Tariffs and Trade (GATT).

As part of the arrangement, the US dollar was pegged to gold at $35/ounce but was later increased to $40/ounce and persists during the Cuban Missile Crisis, Vietnam War and 'Great Society' social programs (Escrivá *et al* 2008). Due to the shortage of gold and inability to maintain gold peg, the run on gold became inevitable thereby leading to the devaluation of the British pounds sterling and US dollar. This era was however overburdened with many exchange rate constraints which became unsustainable at some point because of divergent macroeconomic policies of member states of the Bretton Woods system.

Another rule made capital control an integral part of the agreement which substantially restrained financial flows among countries. Subsequently, there was a growing scepticism about the stability of the exchange rates and the viability of the Bretton Woods system was being threatened by the surging US balance payment deficit, rising capital mobility and the insufficiency of international reserves (Eichengreen and Sussman, 2000). The period ended on 15th August 1971 when the US singlehandedly aborted convertibility of the US dollar to gold (that is, fixed exchange rate regime was abolished), thereby making the US dollar a fiat currency and at the same time a reserve currency for many countries. This has been referred as the "Nixon Shock" in common parlance.[18] This action resulted in countries with fixed exchange rates policy switching to freely floating fiat currencies including the British pound sterling. The collapse of the Bretton Woods agreement has been attributed to expansionary fiscal and monetary policies among developed economies. Figure 2.2 shows a steady rise in stock prices of both countries in the immediate post-World War II. This can be attributed to the 1948 Marshall Plan implemented by the US to boost rapid economic recovery of UK and other European countries devastated by the war. However, the financial markets turned bearish between 1969 and 1970 because of unstable macroeconomic environment.

[18] President Nixon unilaterally jettisoned the system of fixed exchange rate regime when it was no longer economically sustainable.

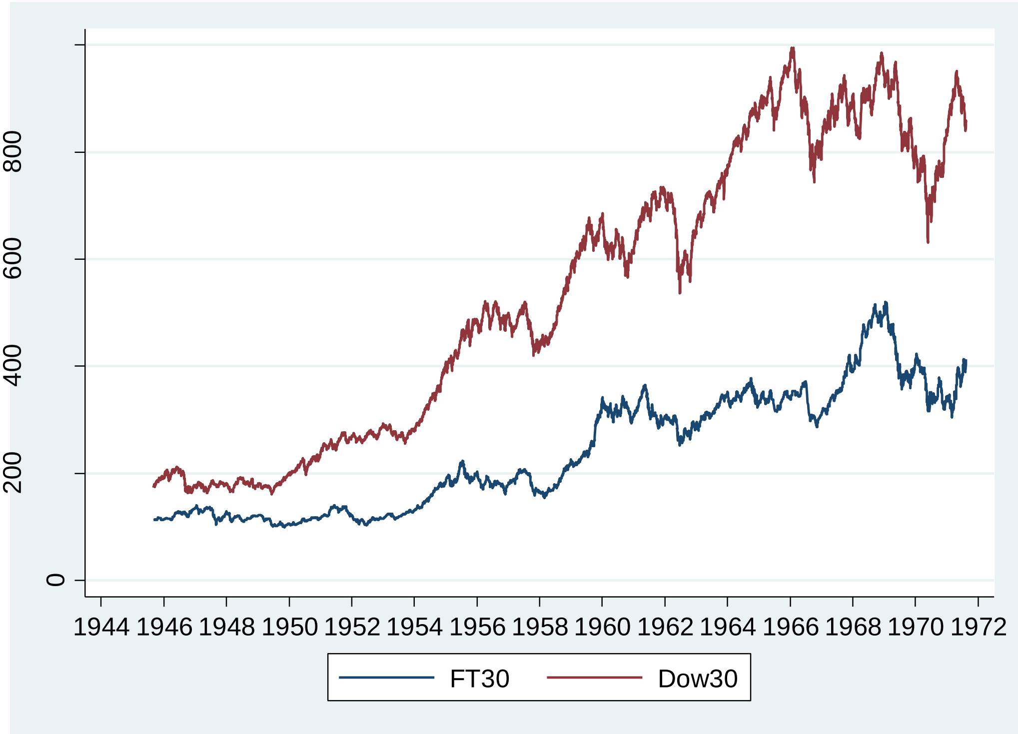


Figure 2.2 FT30 and Dow30 Indices in Period of Bretton Woods System

C. The Period of Pre-1979 UK Exchange Controls (16 August 1971 – 23 October 1979)

The departure from the economic objectives agreed by member countries caused a collapse of the Bretton Woods rule-based international monetary system. The aftermath of the breakdown caused soaring inflation, high budget deficits and rising public debts in the 1970s and 1980s. Since the abolition of the agreement, there have been increasing capital mobility, significant exchange rate flexibility and plummeting monetary price of gold (Eichengreen and Sussman, 2000).

Exchange controls have been in practise in the UK for many decades. However, we are concerned with the exchange controls after the collapse of the Bretton Woods agreement until it was abolished in October 1979. The main reason for exchange controls was to conserve and expand the gold and foreign currency reserves for the purpose of achieving upmost national benefit. Since the end of the Second World War, the UK government has been implementing a systematic gradual removal of exchange controls which though gave rise to capital flows but to a limited extent. Figure 2.3 reveals a sharp decline in stock prices from 1973 to 1975 which can be attributed to the global oil shock of 1973/1974 and the ensuing economic recession in UK, US and other developed economies.

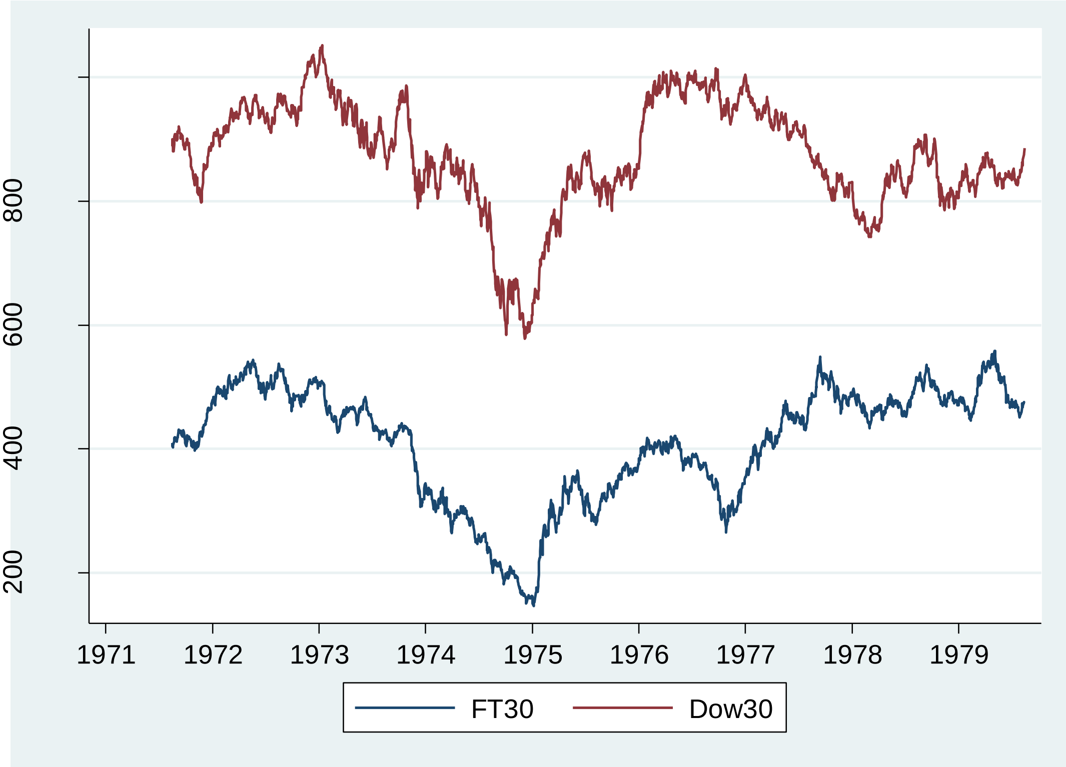


Figure 2.3: FT30 and Dow30 Indices in Pre-1979 UK Exchange Controls Period

D. The Period of Post-1979 UK Exchange Controls (24 October 1979 – 30 June 1990)

Since the collapse of the Bretton Woods Agreement in 1971 and the ensuing financial liberalisation in many developed economies, investors have painstakingly considered the importance of financial globalisation in portfolio investment.[19] The new wave of international financial liberalisation in the developed economies also caused the abolition of capital control in UK.[20]

The exchange controls that placed restrictions on capital movements in the UK was abolished on 24 October 1979 by the newly elected Conservative government. The abolition has increased investors' appetite to trade in foreign assets after nearly 50 years of controlled capital flows between UK and the international economy. The lifting of controls on outward portfolio investment resulted in increase of annual average outward flow from £258 million in the period 1975 - 1978 to £4,890 million in the period 1980 – 1983 (Manser and Bannock, 1985). This

[19] Financial liberalisation is the process of allowing inward and outward foreign equity investment (Bekaert and Harvey, 2003).

[20] Kearney and Lucey (2004) argue that liberalisation has culminated in the removal of price restrictions and domestic quantity, substantial international involvement in domestic financial markets, further cross-border capital flows and new financial instruments.

period marked series of changes to the regulation of the financial markets but the most striking was the new gilt-edged market structure (popularly known as "Big Bang") which began on 27 October 1986. The rapid deregulation of the financial markets stimulated increase in market activity caused by influx of new firms into the gilt market. This period is unique given the significant inflow by foreign institutional investors to the UK financial market, hence the abolition of exchange control will have an impact on the degree of integration between UK and US stock markets.

Since the removal of capital controls by the UK government, the level of capital inflow and outflow rose astronomically. Figure 2.4 depicts the rapid increase of stock prices after all capital controls were removed thereby paving way for cross-listing of stocks and greater portfolio investment in the stock markets. However, there was a sharp decline of UK and US stock prices due to the effect of the unexpected stock market crash on 19th October 1987, popularly referred to as the "Black Monday." This price shock remains the largest fall in stock index prices, which led Dow30 to shed 508 basis points while FT30 dropped by 184 basis points.

Many commentators have argued that financial liberalisation improved efficiency in capital allocation, promoted the rapid development of the financial market and enhanced economic productivity and growth. Nevertheless, some critics of financial liberalisation have argued that it has been behind the major financial and economic crisis suffered since the past two decades, for example, Tequila crisis, Asian crisis in 1997, Russian crisis in 1998, and global financial crises in 2007/2009. Despite these criticisms, Kaminsky and Schmukler (2008) argue that the removal of capital controls may trigger in the short run, financial booms and busts if the time-varying nature of the financial liberalisation is considered, while economies that exhibit significant distortions in the financial markets may subsequently experience collapse in output. Similarly, Syllignakis and Kouretas (2011) argue that in the long run, financial liberalisation may lead to institutional development and accountability of investor thereby facilitating financial and economic stability.

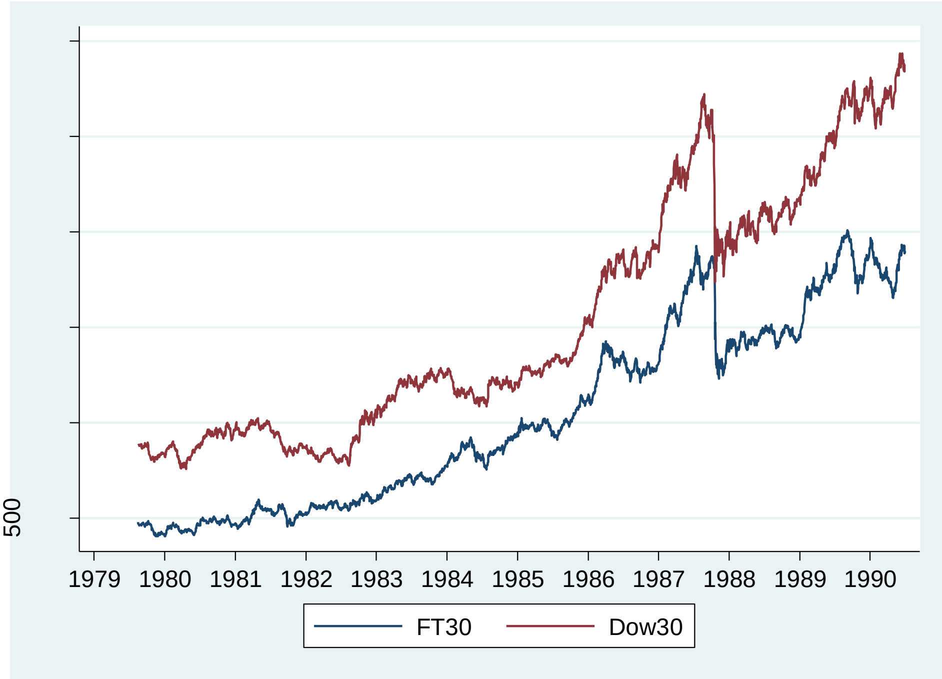


Figure 2.4: FT30 and Dow30 Indices in Post-1979 UK Exchange Controls Period

E. The Period of Pre-EMU (1 July 1990 – 31 December 1998)

The UK joined the European Economic Community (EEC) on 1st January 1973, which later metamorphosed to European Union (EU) on 1st November 1993. There were lot of reforms put in place by the EU to foster financial and economic integration among member states. This period set three stages leading to the establishment of the euro currency. The first stage began from 1st July 1990 to 31st December 1993. During this stage, exchange controls are abolished and the Treaty of Maastricht in 1992 sets a number of economic convergence criteria in readiness for the upcoming monetary union of member countries of EU. Then, the treaty effectively went into force 1 November 1993. The stage two commenced from 1st January 1994 to 31 December 1998. During this stage, European Monetary Institute was established as a forerunner of the European Central Bank (ECB). The member states are also obliged to adhere to the Stability and Growth Path (SGP) adopted in June 1997 as a means of ensuring price stability and fiscal responsibility.

The five convergence criteria to be met by minimum of seven nations before the commencement of the monetary union on January 1, 1999 include; [21]

[21] The fiscal criteria consist of both a debt criterion and a deficit criterion.

1. *HICP Inflation* (12-months average of yearly rates) - shall not exceed the unweighted arithmetic average of the identical Harmonised index of consumer prices (HICP) inflation rates in the three EU member states with the HICP inflation plus 1.5%.
2. *Long-term interest rates* (average yields for 10-year government bond in the previous year) - within 2% of the unweighted arithmetic average of the similar 10-year government bond yields in the three EU member states with the lowest HICP inflation.
3. *Exchange Rate Stability* - Currency within the 2.25% of ERM band under the EMS for two consecutive years, and no devaluation in the previous two years.
4. *Government Budget Deficit* - Budget deficit to GDP ratio at market prices not exceeding 3% at the end of the previous fiscal year and neither for any of the two subsequent years.
5. *Government debt-to-GDP ratio* – the ratio of gross national debt to GDP at market prices not exceeding 60% at the preceding year.[22]

On 3rd May 1998, the eleven member states that will participate in the third stage from 1st January are selected and the ECB was created in 1998. Apparently, UK did not join the third stage of the EMU by exercising the 'opt-out clauses set down in relevant Treaty protocols. In fact, a survey of major issues in EU conducted in October/December 1995 revealed 56% voted against UK joining the EMU in 1999 while 32% voted in support (Issing, 2008).

This period witnessed the most extended period of high rates of economic growth, reduced unemployment, low inflation and general stable macroeconomic fundamentals in the UK and US. The major crises in this period were the 1992 European currency crisis and the Mexican devaluation crisis. Table 2.1 reports the macroeconomic and financial indicators of the Euro area, UK and US before the introduction of Euro currency. In all respect, the US economy presents a better outlook than the UK except in the areas with high deficit budget, massive borrowing and high long term interest rates. Figure 2.5 demonstrates a sharp rise in Dow30 and a very sluggish rise in FT30.[23] Both economies experienced boom during this period and their financial market were relatively calm.

[22] Particularly, the ceiling for budget deficits and government borrowing is fundamental to preventing the 'crowding-out' effect of private investors' access to financing and contributing substantially to economic growth (Valdez and Molyneux, 2010).
[23] FT30 stock index has been superseded by FTSE100 since it was formed in 1984

Table 2.1: Characteristics of Major Economies before Euro Establishment

Characteristics	Reporting period	Unit	Euro Area (11)	United Kingdom	United States
Population	1998	million	315.5	58.49	275.9
Economic Growth rate	1998	% change in real GDP	4.30	3.57	4.45
GDP per capita	1998	Per $	21,921	31,923	38,394
Total Export	1998	% of GDP	33.06	26.25	10.28
Total Import	1998	% of GDP	31.26	26.89	12.28
Debt to GDP	1998	% of GDP	72.94	39.50	59.82
Stock market cap.	1998	% of GDP	62.86	160.7	275.9
Exchange rate	1998	Per $	1.14	1.67	1.00
CPI inflation	1998	% change	2.11	1.60	1.60
Unemployment rate	1998	(% of labour force)	10.20	6.20	4.60
Broad money growth (M2)	1998	% change	5.40	20.85	9.60
Monetary Policy Rate	1998	% interest rate	3.37	5.20	5.56
Ten-year govt. bond	1998	% interest rate	3.95	4.52	4.65
Cash/surplus deficit	1998	% of GDP	-2.16	0.16	-0.05

Source: Federal Reserve Bank of St. Louis

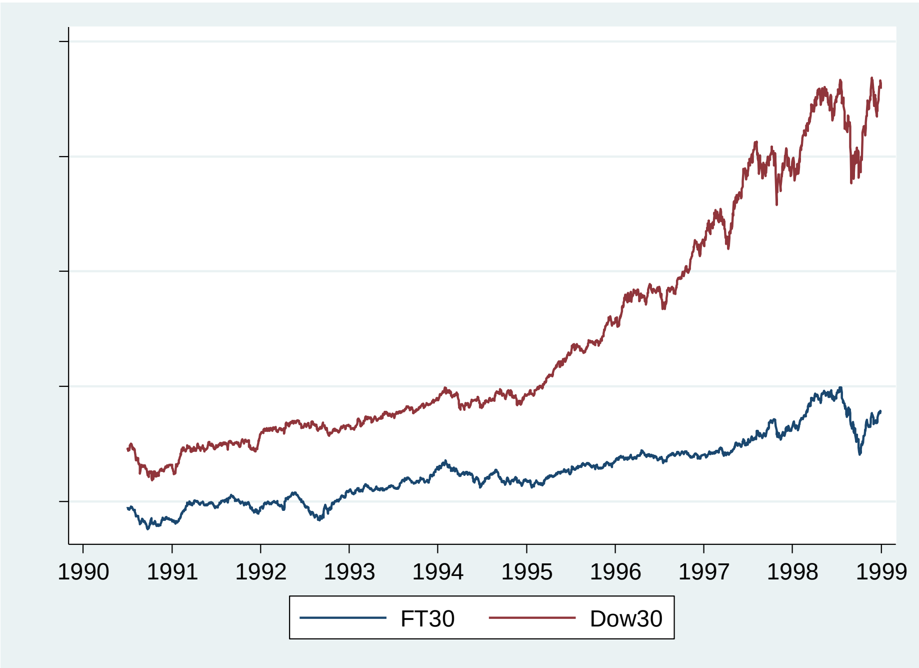


Figure 2.5: FT30 and Dow30 Indices in Pre-EMU Period

F. The Period of Post-EMU (1 January 1999 – 30 June 2015)

The birth of the Euro currency on 1st January 1999 is one of the most significant episodes in modern economic history especially the symbolic achievement of a largest currency area among eleven member states of the EU.[24] The supranational institution responsible for the management and administration of a single monetary policy is under the authority of the European Central Bank (ECB). Indeed, the UK economy has significant ties with the members of EMU because of its EU's membership. After the launch of the euro, the Bank of England (BoE) joined the EU-wide TARGET RTGS (Trans-European Automated Real-time Gross Settlement Express Transfer System - Real Time Gross Settlement) payment system for euro-denominated cross-border transfers.

The Eurozone countries remain the largest trading partner with the US and UK economies, while the US has substantial economic relations with the EU. Many commentators argue that the establishment of EMU has removed exchange rate risk, reduced transaction costs, expanded international trade, increased capital flows, stimulated investment and economic growth. Recent empirical studies have found that the introduction of euro has resulted in close linkages of financial markets of Eurozone and major international financial markets, including the UK and US stock markets (see Cappiello *et al.* 2006; Savva *et al.*, 2009). We may argue that the movement towards regional integration will further enhance the integration of the global economy.

The importance of the pre- and post-euro dates is to understand the nature of integration between US and UK stock markets before and after the emergence of the EMU. The euro currency is currently the most traded after the US dollar and therefore the stability of the euro to a large extent will influence the stability of the international financial markets. According to Morana and Beltratti (2002), the establishment of euro is macroeconomic news of differing importance to various countries which under no condition has engendered a revolution in the economic structure. It would be interesting to understand how the introduction of the euro currency is instrumental to the integration of UK and US financial markets.

[24] The eleven founding fathers of euro currency include Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain. Eight other countries have joined till date, Cyprus, Estonia, Greece, Latvia, Malta, Slovakia, Slovenia and Lithuania. Romania will officially join on 1st January, 2019. Denmark negotiated exemption while Sweden rejected the adoption of the euro based on the result of the 2003 referendum. Some other countries have failed to meet up with the convergence criteria; they include Bulgaria, Croatia, Czech, Hungary and Poland.

Table 2.2 summarises the characteristics of the Euro area, UK and US after the adoption of the euro currency. Comparing Table 2.1 and Table 2.2, we see improvement in the areas of GDP per capita income and international trade, though economic growth, unemployment rate, stock market capitalisation and debt-to-GDP ratios have not been too impressive. Particularly, stock market capitalisation-to-GDP ratio has significantly dropped from the pre-euro period to post-euro period in the Eurozone, UK and US. Figure 2.6 shows stock price movements since the establishment of the Euro Area, thus depicting the stock market boom from 2003 caused by housing market bubble which later crashed, leading to stock market crisis of 2008/2009. In order to avoid the ensuing economic recession from leading into economic depression, fiscal and monetary measures were implemented to stimulate the economy. This has led to a bullish stock market since 2009 particularly with the implementation of the quantitative easing policies of the Central Banks. There are other "extreme" events that occured during the period including the dot-com bubble bust, September 11, 2001 terrorist attacks and Eurozone debt crisis.

In summary, the collapse of the fixed exchange rate regime in 1971 culminated into the adoption of floating exchange rate regime. Indeed, currency floats in the new paradigm act as an adjustment mechanism such that macroeconomic policies are geared towards controlling inflation, deepening financial markets and stimulating economic growth. The stock prices of UK and US have followed similar patterns over time which makes the investigation of the dynamic of financial integration important to practitioners and policymakers.

Table 2.2: Characteristics of Major Economies after Euro Establishment

	Reporting period	Unit	Euro Area (18)	United Kingdom	United States
Population	2014	million	334.0	64.51	321.1
Economic Growth rate	2012	% change in real GDP	1.800	0.280	2.780
GDP per capita	2013	Per $	38,167	37,569	45,341
Total Export	2012	% of GDP	43.56	31.78	13.52
Total Import	2012	% of GDP	40.58	33.92	16.89
Debt to GDP	2013	% of GDP	90.70	132.7	103.3
Stock market cap.	2012	% of GDP	51.67	122.7	114.9
Exchange rate	2013	Per $	1.330	1.640	1.000
CPI inflation	2014	% change	1.350	1.500	2.100
Unemployment rate	2013	(% of labour force)	11.80	7.900	8.100
Broad money (M2)	2014	% change	3.000	0.770	5.020
Monetary Policy Rate	2013	% interest rate	0.270	0.07	0.260
Ten-year govt. bond	2013	% interest rate	3.010	3.09	2.900
Cash/surplus deficit	2012	% of GDP	-3.450	-7.580	-7.520

Source: Federal Reserve Bank of St. Louis

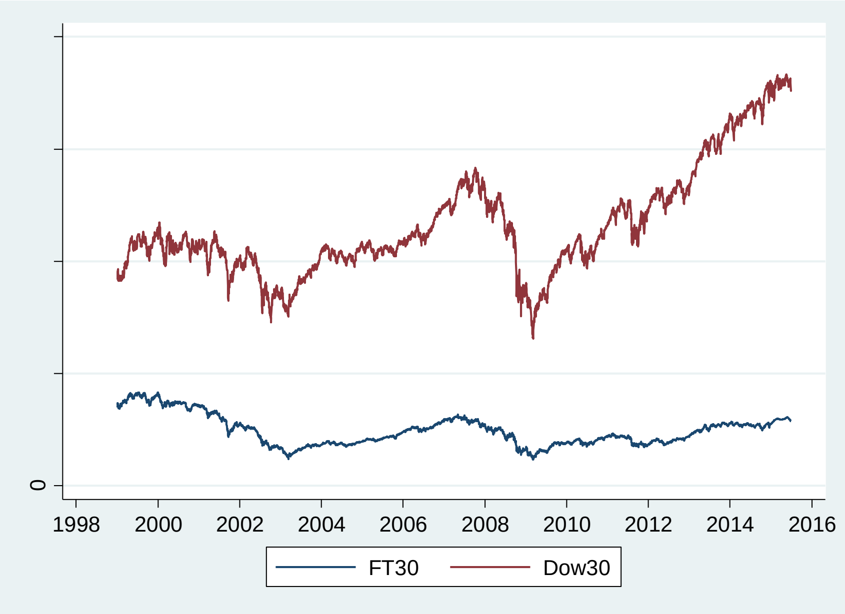


Figure 2.6: Plots of FT30 and Dow30 Indices in Post-EMU Period

2.2.3 *Determinants of Stock Market Integration*

Theoretically, why do macroeconomic and financial variables predict stock returns? In dynamic asset pricing models, the state of the economy in the future is the fundamental driver of time-varying expected stock returns (Neely *et al*., 2014). According to Pretorius (2002), stock market integration can be explained under three categories. The first category is referred to as '*contagion*' effect, which suggests stock market integration that cannot be explained by economic fundamentals or excessive correlations (see, Wolf, 1998; Forbes and Rigobon, 2002; Bekaert *et al*., 2005, 2014). The second category is called '*economic integration,'* which implies stock market integration caused by integration of two economies (e.g. bilateral trade ties, interest rates, inflation and other macroeconomic factors). The final category is described as '*stock market characteristics,'* which are features such as industrial similarity, market volatility and size that influence stock market integration. We conjecture that if the changing macroeconomic conditions are being tracked by these variables converging between the two economies, then they should have predictive power for stock market integration. In this chapter, the three categories are covered and explained on the basis of available data as follows.

A. Macro-Finance Factors

Given the time variation of correlation, these key economic and financial fundamentals may drive the stock market integration process. According to Bracker *et al.* (1999), the greater divergence in real interest rates, inflation rates or currency valuation is likely connected with less co-movement across capital markets. The macro-finance factors that may potentially explain stock market integration include, industrial output growth, bond yield spread, consumer price inflation, exchange rate, gold and oil prices.

(1) Business Cycle Convergence

The industrial production growth is used as a proxy for business cycle convergence. The existing empirical evidence has detailed the relationship between the co-movement of business cycle fluctuation and international financial market correlation. For instance, Phengpis *et al.* (2004) find that correlation of the business cycles is the main driver of stock market integration. According to Kim *et al.* (2005), when countries are in similar phases of business cycle, the degree to which shocks will be transmitted across financial markets will increase, hence providing impetus for the integration process. Similarly, Syllignakis and Kouretas (2011) find that business cycle conditions are connected with stock market correlations (see also Büttner and Hayo, 2011). In contrast, Kizys and Pierdzioch (2006) find no clear linkage between international stock correlations and business cycle convergence. Therefore, if there is convergence (divergence) in the industrial output growth between the UK and US, then their stock market performances should converge (diverge) as well. The conditional correlations between US and UK industrial output are captured using the dynamic conditional correlation (DCC) GARCH model. It is expected that the higher the business cycle convergence, the higher the stock market integration.

In order to examine the phase of the business cycle, we use dummy variables for UK and US boom and recession in our analysis. According to Cai *et al.* (2009), higher/lower stock correlation emerges when both countries experience a contractionary/expansionary phase or higher/lower volatility. Empirical findings show that higher degree of financial integration persists when both countries or the dominant country are in periods of recession (see Erb *et al.*, 1994; Ragunathan *et al.*, 1999; Büttner and Hayo, 2011). We expect that a contractionary or recessionary phase should increase integration.

(2) Interest Rate Convergence

The bond yield spread is used as a proxy for interest rate convergence. The yield spread is captured by the difference between 10-year government bond yields and 3-month Treasury bills. If the bond yield spread of UK and US converge (diverge), as a result of similar (dissimilar) monetary policies, then the effect will cause their stock markets to converge (diverge). For instance, Kim *et al.* (2005) find that convergence towards single interest rate has significantly increase integration. Similarly, Ehrmann *et al.* (2011) find evidence of linkages between interest rates and equity returns across global markets. Syllignakis and Kouretas (2011) find strong evidence of a positive relationship between the interest rate convergence and stock returns correlation. Conversely, Wang and Moore (2008) show an absence of the impact of monetary convergence on stock market integration. The conditional correlations between US and UK bond yield spreads are obtained using the DCC GARCH model. It is expected that a stronger interest rate convergence will cause a higher stock market integration.

(3) Inflationary Convergence

The change in consumer price index (CPI) is used as a proxy for inflationary convergence. Again, the higher the convergence (divergence) between UK and US inflation rate, the higher the convergence (divergence) in their stock markets to integrate. For instance, Kim *et al.* (2005) find that consumer price inflation has contributed to the phenomenal rise of stock markets between EMU and US. Syllignakis and Kouretas (2011) find strong evidence of a positive relationship between the inflationary convergence and stock returns correlation. The conditional correlations between US and UK inflation rates are captured by the DCC GARCH model. We expect that a higher inflationary convergence will propel stock market integration.

(4) Real Exchange Rate Volatility

The conditional volatility of real exchange rate[25] is computed using GARCH (*1,1*) model and is used as a proxy for exchange rate volatility.[26] Theoretically, there is an inverse relationship between stock market correlation and exchange rate volatility because exchange rate risk is a critical source of risk priced on financial markets (see Dumas and Solnik, 1995; Bodart and Reding, 1999; Fratzscher, 2002). For instance, Fratzscher (2002) argues that the more turbulent and unpredictable exchange rates are, the more expensive hedging against such uncertainty is, the stronger the degree of market segmentation and the lower the degree of cross-markets correlation. Kim *et al. (*2005) find that reduction in conditional foreign exchange volatility increases stock market integration. Syllignakis *et al.* (2011) find that exchange rate movements

[25] The real exchange rate is computed as (nominal exchange rate ($/£) multiplied by UK CPI) / US CPI.
[26] Two theoretical explanations for the relationship between stock prices and exchange rates are the international trading effects (Aggarwal, 1981) and the portfolio balance effects (Bahmani-Oskooee and Sohrabian, 1992). For the *international trading effects*, exchange rate depreciation will impart positively (negatively) on export (import) firms thereby increase (decrease) their stock prices. For the *portfolio balance effect*, when the stock market of a country becomes attractive to foreign investors, international capital will flow into the country, thereby leading to a surge in the stock market and further lead to appreciation of the currency.

have significant impact on stock market integration, though positive in some periods and negative in other periods (see also, Büttner and Hayo, 2011). These empirical results support the theoretical arguments put forward by Fratzscher (2002) and Morana and Betratti (2002). Contrary to most empirical findings, Wang and Moore (2008) find a positive link between exchange rate volatility and stock market integration. Therefore, it is expected that the lower the volatility in bilateral exchange rate, the higher the degree of stock market integration.

(5) Commodity Price Volatility

The crude oil and gold markets play significant role in the commodity markets. The conditional volatility of oil and gold prices are computed using univariate GARCH (*1,1*) models and are used as a proxy for commodity price volatility. The gold standard system has been in practice many years ago but between 1945 and 1971, the international monetary system was designed to tie each country's currency to gold under a Bretton Woods arrangement of fixed exchange rate regime. In the financial markets, many investors choose gold as a safe haven asset if other assets exhibit extreme negative returns. However, gold might not be a safe-haven asset especially if it co-moves with other risky assets, such as stocks, real estate etc. According to Baur and Lucey (2010) and Baur and McDermott (2010), gold is a hedge against stocks on average and a safe haven in extreme stock market conditions or negative market shocks. Traditionally, investors have used gold as a hedge against dollar depreciation or rising inflation. For instance, Capie *et al.* (2005) find evidence of the exchange rate hedging potential of gold, whereas McCown and Zimmerman (2006) show evidence of the inflation-hedging potential of gold.

For the petroleum industry which rose to prominence in the 19th century, both economies have been traditionally net importers of crude oil and usually falling oil price and volatility tend to be positive for them. Crude oil is the most widely traded commodity in the world and oil prices have gradually become volatile owing to the intensely competitive nature of the deregulated oil market in the developed economies. It is important to note that shocks to the oil market are global shocks and is affected by economic and institutional factors such as business cycle fluctuations, OPEC oil production policy and occurrence of extreme political events. It therefore means that oil price volatility will have impact on the real economy via consumer and firm behaviours, hence the link between energy and stock markets. Some findings have shown that there is no consensus about the relationship between stock market and crude oil market (see Sadorsky, 1999; Ciner, 2001; Park and Ratti, 2008; Kilian and Park, 2009).[27]

Fundamentally, intermittent changes in commodity prices (oil and gold) are associated with higher volatility. According to Chan *et al.* (2011), stock market downturns correspond with decline in oil and housing prices as investors generally prefer safe-haven assets such as treasury bonds and gold. Therefore, increasing volatility may escalate macroeconomic risk, hence exacerbating financial market instability. We expect that the lower the volatility in the commodity prices, the higher the degree of stock market integration.

B. Stock Market Characteristics

The characteristics of the stock markets may potentially influence the extent of stock market integration. In this session, we consider the impact of stock market volatility and changes in index constituents on stock market integration.

(1) Stock Market Volatility

Volatility is a measure of risk and it remains an important feature of the stock market. High stock market volatility arises when economic agents are very uncertain about the future. The risk-return trade-off is based on the principle that investors will be compensated with higher return for taking additional level of risk. Since international investors always react to information, it is expected that if the volatility is more or less the same in two markets, then returns should be more or less the same in these markets. This suggests that if the volatility of one market increases relative to the volatility of another market, then the returns of the first market should increase relative to the returns of the second market. Therefore, convergence (divergence) in stock market volatilities will cause stock prices to converge (diverge). For instance, Cai *et al*. (2009) find significant relationship between stock correlations and stock volatility. Contrarily, Pretorius (2002) finds insignificant relationship between stock market volatility and stock market correlation. The stock market volatility is measured as the ratio of the conditional variances (derived from ASY BEKK model) of the UK and US stock returns. We expect that the lower the stock market volatility the higher the stock market integration.

[27] Oil price shocks can affect the discount rate for cash flow by influencing the expected inflation rate and the real interest rate (Miller and Ratti, 2009).

(2) Composition of Stock Index

The nature of industrial similarity may influence the integration process of stock markets. For instance, Serra (2000) finds that cross-market correlation is not affected by the industrial composition of the indices. In this chapter, we capture how changes in index composition influence stock market integration using dummy variables. Since 1935, the constituents of the Dow30 index have changed 19 times, whereas that of FT30 index have changed 56 times. This perhaps suggests that the FT30 index may relatively be unstable when compared to the Dow30 index. Assuming similar industrial composition, we expect that changes in FT30 or Dow30 indices may drive stock market integration.

C. Non-Economic Fundamentals: Political and Economic Episodes

There are various historical episodes in the last eight decades that may influence the linkages of international stock markets. These political, economic or financial events might have shaped the stock market integration of Anglo-America way of financial capitalism.

(1) Political Episodes

In retrospect, the world has been ravaged with all kinds of political crises and wars in great proportion. Within the last century, the US has emerged the global superpower while both UK and US are members of the Security Council of the United Nations. They share similar political, military and diplomatic ties which have culminated in both countries having joint involvement in external political conflicts. Both countries have been overtly or covertly involved in political conflicts and wars with other countries. Starting from the Second World War, the intervention of US in 1942 bolstered the alliance between the US and UK which climaxed into victory in 1945. Immediately after the Second World War, the tussle for world dominance between the two superpowers, namely US and Union of Soviet Socialist Republics (USSR) led to a period of Cold War. The battle of political and economic ideologies was between US, UK and other anti-communist allies on the one hand, and USSR, China and other communist allies, on the other hand. The proxy conflicts between these two ideological groups were played out during the Korean War (1950 – 1953) and the Vietnam War (1955 – 1975). The ideological war started to wane when many countries embraced Western democracies, which was caused by the internal contradictions in USSR and the eventual dissolution of the Soviet Union in 1991.

Subsequently, international conflict shifted to the middle-east when Iraq invaded Kuwait in 1990, leading to the US and other coalition forces intervening to liberate Kuwait. The Gulf war of 1990/1991 precipitated economic disruptions in many countries after the consequent rise in oil prices. Afterwards, there was relative tranquillity in global politics until the September 11, 2001 attack of the World Trade Centre and Pentagon in US by the Al-Qaeda terrorist group. This attack provoked the US to launch the war on terror and invaded Afghanistan to dethrone the Taliban who provided safe-haven for Al-Qaeda. The war which began since 2001 was led by US, UK and other allies, and finally ended in 2015. In a similar fashion, the allied forces invaded Iraq in 2003 on the pretext of Iraq's possession of weapons of mass destruction. The war was ended in 2011 after the withdrawal of all US troops. These are the major international conflicts that the US and UK have participated in and we expect because of the economic cost in financing these wars, there may be a link to the integration of their stock markets.

(2) Financial and Economic Episodes

The US and UK economies have been hit by several financial and economic crises, bubbles and busts for many decades. Since the world economic depression of the 1930s, there have been several crises until the world economy was hit again with global financial crisis between 2007 and 2009. To begin with, immediately after the Second World War in 1945, the developed economies suffered post-war slump from 1945 to 1949. Then, the implementation of the 1948 Marshall plan in Europe resulted in rapid economic growth and development of many developed countries. Afterwards, the first major OPEC oil shocks (1973/1974) created economic imbalances, worsened unemployment and generated financial markets instability in the 1970s.[28] After a period of relative calm of the financial markets, the stock markets crashed suddenly in October 1987 in most developed countries. Market analysts attributed the cause of the crash to program trading strategies, stock overvaluation, market illiquidity and market psychology (see Bozzo, 2007; Bookstaber, 2007; Annelena, 2007). Although, the market recovered after a while, huge investment value was eroded within days of the crash.

Thereafter, UK's entrance into the ERM was short-lived during the European currency crisis of 1992/1993, thereby leading to its withdrawal to form a common European currency. Another economic crisis that US got involved in was the bailout package for Mexico during the Mexican currency crisis (also known as 'Tequila episode') of 1994-1995. The Clinton Administration used American funds and pressured the IMF to use its fund to bail out the country in order to avert the crisis spreading to other Latin American countries.

[28] The oil crisis was triggered by the Yom Kippur War in which the Arab members of OPEC initiated an oil boycott leading to significant increase in the world price of oil. The crisis produced simultaneous recessionary and inflationary pressures in the developed economies.

Subsequently, the Asian currency crisis in late 1997 and the Russian debt default crisis of summer 1998 hit the globe and resulted in the collapse of Long-term Capital Management (LTCM), a leading hedge fund in US.[29] The empirical finding by Wang and Moore (2008) evince a positive relationship between stock market integration and 1997/1998 Asian and Russia crisis. The advancement of information technology (IT) caused an influx of high-growth IT stocks in the US and many OECD economies (including the UK). The dot-com bubble (1997 – 2000) increased investors' appetite for the stock market. Eventually, when some investors discovered that many IT stocks were overpriced, there was market panic which resulted into dot-com bubble bust in March 2000 and continued until September 2002.

After a relative calm in the financial market, the Bank of England (BoE) and Federal Reserve (Fed) gradually lowered the monetary policy rate, which triggered the housing bubble in the UK and US especially from 2005. When the stock market reached the peak as a result of overpriced stocks, then another market crash became inevitable. The global financial crisis (GFC) that began in 2007 led to the 2008 stock market crash after the collapse of global financial firms including, Lehman Brothers, AIG, Merrill Lynch etc. The crisis spilled over to European banks and resulted in general decline of major stock indices and commodities all over the world. Despite the sharp fall in stock prices and high volatility, the stock markets never stopped functioning. Some analysts have argued that the ensuing credit crunch leading to GFC started from August 2007 and ended on March 2009.[30] The reason was as a result of the negative announcements by the investment bank Bear Stearns and BNP Paribas which caused deterioration of liquidity in the money markets, hence leading to substantial Central Bank interventions (see Baur, 2012; Taylor and Williams, 2008). The end of the GFC was signalled by the absence of negative news and a stock market rally (Baur, 2012).

In order to curtail the severity of the GFC, the US and UK governments introduced the programme of asset purchases, commonly referred as 'quantitative easing' (QE). The BoE and Fed used conventional and unconventional monetary policies to combat the recent global economic meltdown. QE began in March 2009 till October 2012, with a total investment of £375 billion by BoE. In the case of the US, QE began from November 2008 till date with a total of investment of about £2.5 trillion.[31] The QE is simply a measure of purchasing assets

[29] The sudden capital outflows after a period of private overinvestment triggered the 1997 East Asian crisis.
[30] In 2008, Lehman Brothers filed for bankruptcy, Bank of America was purchased Merrill Lynch, and Fannie Mae and Freddy Mac was nationalised in US. In UK, the government bailed out RBS, HBOS and Lloyds TSB in 2008.
[31] The Fed started with QE1 from November 2008 to April 2010 with a total investment of $1.7 trillion. After adjudging it as successful, the Fed rolled out QE2 from November 2010 to June 2011 by spending $85 billion each month. Recently, they commenced with QE3 by spending $40 billion each month.

(substantially government securities and minimal private assets) through the secondary markets with central bank money (Joyce *et al.*, 2011).[32] The QE is designed at reducing borrowing costs, increasing liquidity, stimulating nominal spending, boosting economic growth, reducing unemployment rate and achieving inflation target. We expect that QE policies should make their stock markets rebound from an economic downturn and stimulate market integration.

The monetary and fiscal measures introduced by sovereign states to stimulate economic recovery further led to the sovereign debt crisis in the Euro area from 2010. The difficulties of funding their debts have led to credit rating downgrades and further increased the cost of borrowing. Since the Eurozone debt crisis, the "troika" (the European Central Bank, the European Commission and the IMF) have been at the forefront of combating the systemic risks it poses to the global financial system through capital injections, liquidity provisions and guarantees. Regarding the Eurozone debt crisis, some researchers argue that the provision of financial backup by the government to restore confidence has led to moral hazard risk (see Ureche-Rangau and Burietz, 2013). Given all these economic episodes, we expect that they may significantly influence stock market integration.

2.2.4 *Evidence on Cointegration, Spillover Effects and Stock Market Integration*

The evolution of financial integration across international financial markets has been a core subject of debate since the last three decades. Particularly, some suggest strong integration in the financial markets of developed countries while others support less integration. The assumption of financial market integration may be further explained on the basis that higher correlation of stock returns across economies is caused by flows of capital across countries, together with international arbitrage (see Dumas *et al.*, 2003; Tavres, 2009).

To start with the empirical evidence based on cointegration analysis, Taylor and Tonks (1989) find that since the abolition of UK exchange control in 1979, the UK stock market has become cointegrated with overseas countries (Germany, Netherlands, Japan) with the exception of US, suggesting that in the long run these returns are highly correlated, with the implication that international diversification benefits in the long run will be curtailed. Similarly, Kasa (1992) investigates the major international stock markets between 1974 and 1990 and finds cointegrating relationship, suggesting stock market co-movement. In a similar fashion, Floros (2005) investigates the market linkages and cointegration between S&P 500, Nikkei 225 and

[32] The programme is targeted at purchasing medium and long-term bonds in the secondary market with the aim of reducing interest rate to give an additional monetary stimulus to the economy.

FTSE-100 stock indices from 1998 to 2003. He finds that developed markets are cointegrated, indicating a stationary long-run relationship.

In contrast, Kanas (1998) uses the Johansen technique to test for cointegration between the US and each of the six largest European equity markets (UK, Germany, France, Switzerland, Italy and Netherlands) from 1983 to 1996. He finds that the US market is not pairwise cointegrated with any of the European equity markets. Also, Chan *et al.* (1997) investigate monthly stock indices of eighteen equity markets using Johansen cointegration tests and find that small numbers of stock markets are cointegrated with others. They conclude that since the stock markets show limited long-run co-movements then international diversification among them may be effective. More recently, Hatemi (2008) accounts for structural breaks in cointegrating relationship between UK and US, and finds a long run steady relation, suggesting increased integration between them.

Substantial empirical studies on cointegration analysis conducted limited tests and do not account for structural breaks. Given that relationships between stock markets exhibit strong variation over time, the cointegration techniques are inadequate in modelling the dynamic process of stock market integration. Also, the use of long and recent dataset has been given less attention by many researchers. The existing empirical findings on cointegration relationship between UK and US have been mixed, hence, there is need to apply more cointegration tests on a long dataset for the purpose of robustness.

Using the VAR methodology, Ammer and Mei (1996) examine the news components of monthly datasets for US and UK from 1957 – 1988. They find that news about future dividend growth is more highly correlated between countries and there is a closer financial integration between US and UK data after the Bretton Woods currency arrangement was abandoned and Britain suspended exchange controls. In the same vein, Engsted and Taggaard (2004) investigate the nature of co-movement between the UK and US stock markets over the period 1918 – 1999 using VAR model. They find that the main determinant of the volatility of the US and UK stock market is news about future excess returns, which is highly correlated and help to explain the high degree of co-movement between the two markets.

Another perspective of studies on co-movement is focused on identifying the impact of shocks on market correlations. The foundation was laid by King and Wadhani (1990) using the cross-market correlation coefficient approach. They find that the cross-market correlations increased significantly after the US market crash in 1987 between the US, UK, and Japan, suggesting evidence of contagion (see also King *et al.*, 1994; Longin and Solnik, 1995; Baig and Goldfajin, 1999).

From the perspective of volatility spillovers, Hamao *et al.* (1990) find that when post-October 1987 period is excluded from the sample, volatility spillovers become less pervasive across markets, suggesting that volatility spillovers are more pronounced during the market crisis. Similarly, Susmel and Engle (1994) study the interrelationship between the stock markets of US and UK, and find less evidence of either mean or volatility spillovers.

However, Forbes and Rigobon (2002) adjust for heteroskedasticity biases in the correlation coefficient approach and find no increase in unconditional correlation coefficients (that is, no contagion) during the 1997 Asian crisis, 1994 Mexican devaluation and 1987 US market crash. They conclude that there was no contagion in these three periods but rather interdependence because there was high level of co-movement in all periods (see also Bordo and Murshid, 2001).

Baele (2005) uses regime-switching model to investigate volatility spillover effects in European Equity markets, and finds that increased trade integration, equity market development and low inflation give rise to the increase in EU shock spillover intensity. He also finds evidence of contagion from the US to a number of European stock markets during period of high world market volatility.

Goetzmann *et al*. (2005) examine the correlation structure of world equity markets for a period of 150 years and find that correlations between stock markets were relatively high during the periods of economic integration such as the late nineteenth century, the Great Depression and the late twentieth century. They also find that period of free capital flows are associated with high correlations.

Kim *et al.* (2005) use the bivariate EGARCH framework to study the impact of EMU on stock market integration over the period of 1989 to 2003. They find that bidirectional spillover effects between US and major European markets, and further argue that stock market integration has been partly driven by macroeconomic convergence associated with the introduction of EMU and financial development levels.

Caporale *et al.* (2006) examine the international transmission of the 1997 South East Asia financial crisis for US, European, Japanese and South East Asian stock market returns using the bivariate GARCH-BEKK model. They find that volatility spill over in all cases but the dynamics of conditional volatilities differ. They also find that causality links in the variance are strong and bidirectional in normal periods and unidirectional in crisis periods, which they argue to be consistent with crisis-contingent models. Similarly, Cappiello *et al*. (2006) relate an increase in correlation of stock markets in the recent past with the introduction of the euro currency. Hon *et al.* (2007) also find that the technology bubble bust in the US Nasdaq caused an increase in correlation between the US and other foreign stock markets.

Chiang *et al.* (2007) investigate nine Asian daily stock returns from 1990 to 2003 using DCC-MGARCH model. They find an increase in correlation (that is, contagion) and a continued high correlation (that is, herding) during the Asian crisis period (see also, Froot *et al.*, 2001, Bae *et al.*, 2003; Kallberg *et al.*, 2005).[33] The conclusion from the foregoing studies is that increased co-movement of stock market returns of countries during crisis era implies the occurrence of market contagion.

Panopoulou and Pantelidis (2009) study the international information transmission between the US and the rest of the G-7 countries using BEKK model from 1985 to 2004. They find increased interdependence in the volatility of the markets under examination. Analysing further the volatility impulse response, they show that the level of interdependence combined with increased volatility persistence make volatility shocks perpetuate for a significantly longer period in present times compared to the pre-1995 era.

In relation to the introduction of Euro, Savva *et al*. (2009) investigate its impact on the interactions across the stock markets of New York, London, Frankfurt and Paris. Applying the dynamic conditional correlation (DCC) version of the VAR-multivariate EGARCH model, they find the existence of spillover effects from foreign markets for both returns and volatilities, with asymmetries in volatilities and conditional correlations such that negative shocks have considerable impact than positive shocks. The introduction of Euro has a significant impact on cross-market correlations, especially for Frankfurt and Paris, indicating increased integration for these markets.

Aslanidis *et al.* (2010) investigate the co-movements between US and UK stock markets using the time-varying smooth transition conditional correlation (STCC) GARCH specification from 1980 to 2006. They find increased correlations between the two markets from around 1999, which they attribute to globalisation and international financial market integration. They

[33] Chiang *et al.* (2007) describe contagion as the significant increase in correlation between markets arising from spreads of shocks from one market to another, while herding is high correlation coefficients in all markets arising from the simultaneous behaviour of investors across different markets.

conclude that less benefit will be derived from portfolio diversification between the two countries.

Naouis *et al*. (2010) investigate the existence of contagion effect following the US subprime crisis for 6 developed and 10 emerging markets by applying the DCC GARCH model. They conclude that during the crisis period, contagion is strong between US and developed and emerging markets. Similar findings are reported by Hwang *et al.* (2010), Bouziz *et al.* (2012) and Celik (2012).

Karunnanayake and Valadkhani (2011) use the ADVEC MGARCH model to examine the asymmetric effects of stock market volatility transmission using weekly stock market return data of four countries, namely, Australia, Singapore, UK and US. According to their findings, negative shocks in each market play a more significant role in increasing volatility than positive shocks. Also, they find that all markets exhibit significant unilateral positive mean and volatility spillovers from the US stock market returns.

Keneourgious *et al.* (2011) study financial contagion of four emerging markets (Brazil, Russia, India and China) and 2 developed markets (UK and US) using multivariate regime-switching Gaussian copula model and the asymmetric generalised dynamic conditional correlation approach. They find contagion effect from the crisis country to all others for each of the considered financial crises.

Syllignakis and Kouretas (2011) investigate the time-varying conditional correlations to the weekly index returns of seven emerging stock markets of Central and Eastern Europe (CEE) using DCC multivariate GARCH model. They find that there is a statistically significant increase in conditional correlations between the US and the German stock returns and the CEE stock returns, especially during the 2007 – 2009 financial crises, which they referred to as a *contagion effect* and a continued high correlation in the aftermath of the crisis is referred to as *herding*. They further find that conditional correlation is significantly influenced by domestic and foreign monetary variables and exchange rate fluctuations.

Dimitriou *et al.* (2013) investigate the contagion effects of the global financial crisis in a multivariate FIAPARCH DCC framework using a data spanning from 1997 to 2012 for 6 stock markets (Brazil, Russia, India, China, South Africa and US). They find no contagion effects for most BRICS in the early stage of the crisis, implying signs of decoupling. However, they show that correlations increased from early 2009 onwards, suggesting that their dependence is larger in bullish than in bear markets.

Recently on world stock market integration, Berger and Ponzi (2013) use the state space methods that allow for time-varying conditional variances to measure the financial market integration five developed countries (France, Germany, Japan, UK and US). They suggest that over the period 1970 – 2011, the stock market integration increased substantially in all countries except for Japan.

Also, recent study by Bekaert *et al.* (2014) on 2007-2009 global crisis and equity market contagion, find from the perspective of a factor model with global and domestic factors, evidence of contagion. However, the evidence shows weak contagion from US markets to equity markets globally during the crisis whereas, there was strong contagion from domestic equity markets to individual stock portfolios. They conclude that their results provide strong support for the validity of the '*wake-up call effect'* as a transmission mechanism of the 2007 to 2009 financial crisis.

In summary, recent literature has justified increasing stock market integration between UK and US but with limited data structure and empirical analysis. Similarly, the literature reviewed has not considered information asymmetries in the variance and correlation structure for the whole sample period. Also, little attention was given to subsample analysis, which is critical to understanding the long- and short-run dynamics between the two markets. Limited attention has been given to explaining the nature of integration by comparing longer post-EMU period with preceding periods. Indeed, most findings indicate that stock market correlation between the two markets has been increasing, however few empirical evidence has been provided to explain the drivers of the integration process. In fact, no empirical study has ever addressed the change in index constituents as a potential driver of integration. In this study, we aim to establish the dynamic relationship between these markets in a rapidly evolving global political and economic systems, which will have important implications for international diversification decisions and financial market stability.

2.3 Methodology

This session begins by describing the models for testing cointegrating relationship between the two stock markets in section 2.3.1. Then, we proceed to explaining the vector error correction model (VECM) and measure of price discovery in section 2.3.2. The bivariate asymmetric BEKK and DCC GARCH models are described in section 2.3.3. The volatility impulse response function used in measuring the impact of independent shocks on volatility is described in section 2.3.4. Finally, section 2.3.5 explains the mixed data sampling approach for the purpose of evaluating the determinants of the stock market integration.

2.3.1 *Long-run Relationships - Cointegration Tests*

Cointegration measures the long-run common stochastic trend among variables. In other words, it examines the long term behaviour of market prices. According to Dolado (1999), cointegration is defined as the co-movements among trending variables with the capability of testing for the existence of equilibrium relationships within a wholly dynamic specification framework. It can be deduced therefore that if two stock prices are cointegrated, then viable arbitrage profits can be explored when there is deviation from equilibrium.

This chapter adopts the following cointegration tests; Engle-Granger (EG) residual-based test, fully-modified OLS estimator, canonical correlation regression estimator, Johansen technique, and Gregory-Hansen (GH) regime shift test. Cointegration tests that do not account for structural breaks in the time series may lead to low power and bias result. However, the GH regime shift test accounts for structural changes that may shift the long-run relationship of the underlying variables.

A. Engle-Granger Methodology

The necessary condition for cointegration is that the variables should be integrated of the same order. According to Enders (2004). it is possible to find equilibrium relationships among variables that are integrated of different order. Floros (2005) further argues that stock markets are interdependent if the stock indices of two or more countries are cointegrated (that is, they exhibit long-run relationship).

The linear relationship between UK and US stock indices are specified as;

$$lnP_{UK,t} = \alpha + \beta lnP_{US,t} + e_t \qquad (2.1)$$

According to Engle and Granger (1987), if the two price series are non-stationary, but the deviations are stationary, then $lnP_{UK,t}$ and $lnP_{US,t}$ are cointegrated of order (*1,1*). The estimated value of the departure from the long-run relationship is detected by the stationary disturbance term denoted as $\hat{e}_t$. The Augmented Dickey Fuller (ADF) is used to test the disturbance term and is expressed as;

$$\Delta\hat{e}_t = \beta_1\hat{e}_{t-1} + \sum_{i=1}^{n}\beta_{i+1}\Delta\hat{e}_{t-i} + \varepsilon_t \quad (2.2)$$

Having selected the lag lengths, if we fail to reject the null hypothesis $\beta_1 = 0$, then we cannot reject the null of no cointegration. On the other hand, if the null hypothesis is rejected against the alternative $\beta_1 < 0$, then it is concluded that the series are cointegrated of order (*1,1*), thus a form of long-run stock market integration is established.

This residual-based Engle-Granger static long-run regression has been challenged especially for its inefficiency in multivariate cases. According to Banerjee *et al.* (1986), bias in the estimated parameters is likely to be created when lagged terms in small samples are neglected. Blough (1988) further expresses concern about the low power of the cointegration test in relatively small samples.

B. FMOLS and CCR Cointegration Regressions

The fully modified ordinary least square (FMOLS) estimator was proposed by Phillips and Hansen (1990) while the canonical correlation regression (CCR) estimator was proposed by Park (1992). These cointegration regression models use a semiparametric correction to eliminate asymptotic bias and have fully efficient normal asymptotics. They allow the use of standard Wald tests based on asymptotic chi-squared statistical inference. These cointegration regression estimators eliminate asymptotically the endogeneity bias caused by the long-run correlation of y_t and x_t', the second-order bias (i.e. regression errors are serially correlated) of the OLS estimator.

Both FMOLS and CCR estimators can be derived by transforming the regressors and regressand and subsequently applying the OLS procedure (Wang and Wu, 2012).

We start by expressing the time series vector process $(y_t, x_t')'$ with cointegrating relationships as;

$$y_t = x_t'\beta + d_{1t}'\gamma_1 + u_{1t} \quad (2.3)$$

$$y_t = \Gamma_1 d_{1t} + \Gamma_2 d_{2t} + \varepsilon_t \quad (2.4)$$

$$\Delta\varepsilon_t = u_{2t} \quad (2.5)$$

where d_{1t} and d_{2t} are deterministic trend regressors; u_{2t} are regressors innovations. The innovations $u_t = (u_{1t}, u_{2t}')'$ are assumed to be strictly stationary and ergodic with zero means, finite covariance matrix, one-sided long-run covariance matrix Λ, and nonsingular long-run covariance matrix Ω.

The regressand is being transformed under FMOLS as follows;

$$y_t^+ = y_t - \hat{w}_{12}\hat{\Omega}_{22}^{-1}\hat{u}_{2t} \tag{2.6}$$

where $\hat{u}_{1t}$ is the residual of the cointegration equation estimated by OLS, and $\hat{u}_{2t}$ are differenced residuals of regressor equations or the residuals of the difference regressor equations.

The FMOLS estimator proposed by Phillips and Hansen (1990) is given by;

$$\hat{\theta}_{FMR} = \begin{bmatrix} \hat{\beta} \\ \hat{\gamma}_1 \end{bmatrix} = \left[\sum_{t=1}^{T} z_t z_t'\right] \left[\sum_{t-1}^{T} z_t y_t^+ - T\begin{pmatrix} \hat{\lambda}_{12}^{+'} \\ 0 \end{pmatrix}\right] \tag{2.7}$$

where $\hat{\lambda}_{12}^+ = \hat{\lambda}_{12} - \hat{w}_{12}\hat{\Omega}_{22}^{-1}\hat{\Lambda}_{22}$ are called bias-correction terms. $z_t = (x_t', d_{1t}')'$. $\hat{w}_{1,2}$ is the estimate of the long-run covariance of u_{1t} conditional on u_{2t}.

In this study, a constant and a time trend are included in the equation for the FMOLS estimator;

$$lnP_{UK,t} = \beta_0 + \beta_1 t + \beta_2 lnP_{US,t} + u_t \tag{2.8}$$

The quadratic spectral kernel and the Andrews automatic bandwidth selection method are adopted.

The CCR is constructed by adjusting the data using stationary components of a given model. The CCR estimation transforms both the regressand and the regressors as;

$$y_t^+ = \left\{\hat{\Sigma}^{-1}\hat{\Lambda}_2\tilde{\beta} + \begin{pmatrix} 0 \\ \hat{\Omega}_{22}^{-1}\hat{\omega}_{21} \end{pmatrix}\right\}' \hat{u}_t$$

and $z_t^+ = \left(1, z_t^{+'}\right)'$ with $x_t^+ = x_t - \left(\hat{\Sigma}^{-1}\hat{\Lambda}_2\right)'\hat{u}_t$

where $\hat{\Lambda}_2 = \left(\hat{\Lambda}_{12}, \hat{\Lambda}_{22}'\right)'$. $\tilde{\beta}$ is the OLS estimator of β; $\hat{u}_t = \left[\hat{\Lambda}_{1t}, \Delta x_t'\right]'$ comprises of the OLS residuals and the first difference of the *I(1)* regressors. Therefore, the CCR estimator is defined as;

$$\hat{\theta}_{CCR} = \left(\sum_{t=1}^{T} z_t^+ z_t^{+'}\right)^{-1} \left(\sum_{t=1}^{T} z_t^+ y_t^+\right) \tag{2.9}$$

The FMOLS and CCR models transform the data such that OLS eventually give an asymptotically efficient estimators. According to Montalvo (1995), the CCR estimator shows lower bias than the OLS and the FMOLS. The drawback of these methods is the ambiguity created if the system contains more than one cointegrating relation. In this situation, the Johansen technique performs better than other tests.

C. Johansen Technique

The Johansen technique builds cointegrated variables directly on maximum likelihood estimation rather than OLS procedures (Johansen and Juselius, 1988).

The technique is specified by a VAR(p) model as follows;

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon_t \qquad (2.10)$$

where $\Pi = \alpha\beta'$, α and β are $n \times r$ matrices (r is the number of cointegrating vectors). The error correction parameters contained in α measure the degree to which the variable react to disturbances in the long-run equilibrium; the parameter ($\Gamma_i, \ldots, \Gamma_{p-1}$) of dimension $n \times n$ define the short-run adjustment to changes in the variables, which implies the presence of $p - r$ common trends (Gonzalo and Granger, 1995). The variables in y_t are not cointegrated, as long as the rank of Π is zero, thus the characteristic roots will equal zero and no stationary linear combination can be identified.

Johansen techniques provide two statistics to test for the null hypothesis of no cointegration, which are the trace statistic and the maximum eigenvalue statistic. They are specified as;

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \lambda_i) \qquad (2.11)$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \lambda_{r+1}) \qquad (2.12)$$

where T is the number of usable observations; λ_i is the estimated values of the characteristic roots derived from the estimated Π matrix. If the test statistics is greater than the critical value, then the null hypothesis that there are r cointegrating vectors is rejected against the alternative that there are $r + 1$ (for trace) or more than r for maximum eigenvalue (Enders, 2010). This model is useful for determining the number of cointegrating relationships (that is, long-run relationships) among the variables.

Indeed, the Johansen technique is capable of testing long-term relationship. A fundamental drawback of the Johansen method is the symmetrical treatment of all variables in a VAR system, hence makes no clear distinction between endogenous and exogenous variables.

D. Gregory-Hansen Test

The Gregory-Hansen (GH) test has the capability of detecting cointegrating relations when there is a break in the intercept and/or slope coefficients. The power of standard test for the null hypothesis of no cointegration can be significantly reduced if structural changes that manifest through changes in the long-run relationship whether by changes in the intercept or changes in the cointegrating vectors are not accounted for (Gregory and Hansen, 1996). The Gregory-Hansen test for the null of no cointegration against the alternative hypothesis of cointegration while allowing for trend and one-time regime shift of unknown timing.[34] The test has the capability to detect cointegration relationship among variables of interest when there is a break in the intercept and/or slope coefficient. The limitation of Johansen technique and Engle-Granger test to falsely conclude on absence of cointegrating relationship has been overcome by the Gregory-Hansen's test inclusion of a one-time regime shift in the cointegrating vector.

The structural changes of the regime shift model is captured by a shift in the intercept or slope of the cointegrating relationship. Gregory-Hansen (1996) specifies the model as;

$$y_{1t} = \mu_1 + \mu_2\psi_{t\tau} + \alpha_1^{\mathrm{T}}\mu_{2t} + \alpha_2^{\mathrm{T}}y_{2t}\psi_{t\tau} + e_t \qquad t = 1,\ldots,n \qquad (2.13)$$

where, μ_1 denotes the intercept before the shift; μ_2 is the change in the intercept at the time of the shift; α_1 represents the cointegrating slope coefficients before the regime shift; α_1 and α_2 denote the change in the slope coefficient; ψ_t if the dummy variable that captures the structural change (if $t > \tau$, dummy variable is 1; $t < \tau$, dummy variable is 0); $\tau \in (0,1)$ is a relative timing of the change point.

In summary, applying these cointegration tests will help to explore robustly the long-run relationship between UK and US stock markets. Particularly, using cointegration test that identifies structural changes will influence the results of the long-run relationship between variables under scrutiny. However, we give more credence to models that make a clear distinction between endogenous and exogenous variables.

2.3.2 *Vector Error Correction Model*

The Vector Error Correction Model (VECM) captures the responses of stock market returns to the arrival of news. This model captures the dynamic return spillovers between the two markets. If there is cointegrating relationship between the markets under consideration, then the VECM is used to establish their short-run relationships. Given the presence of cointegrating

[34] Regime shift can be described as fundamental or structural changes in policy.

relationship, the error correction model is estimated as a feedback process of deviations adjusting towards long-run equilibrium. The VECM is given as;

$$R_{UK,t} = \alpha_{UK} + \delta_{UK} z_{t-1} + \sum_{i=1}^{p_{UK}} \beta_{UK,i} R_{UK,t-i} + \sum_{j=1}^{q_{US}} \beta_{US,j} R_{US,t-j} + \varepsilon_{UK,t} \qquad (2.14)$$

$$R_{US,t} = \alpha_{US} + \delta_{US} z_{t-1} + \sum_{j=1}^{q_{US}} \beta_{US,j} R_{US,t-j} + \sum_{i=1}^{p_{UK}} \beta_{UK,i} R_{UK,t-i} + \varepsilon_{US,t} \qquad (2.15)$$

where $R_{UK,t}$and $R_{US,t}$ represent UK and US stock returns, respectively. The z_{t-1} is the error correction term and it measures how the dependent variables adjust to the last period's deviations from the long-run equilibrium. The speed of adjustment back to the long-run equilibrium following a market shock is captured by δ_{UK} and δ_{US}, in which at least one speed of adjustment coefficients must be non-zero (that is, one positive and the other negative).

The causal relationship between the two markets is examined by Granger-causality test, which is an *F*-test for the joint hypothesis of zero coefficients of lagged independent variables. For instance, if UK stock returns 'Granger cause' US stock returns, then past values (lags) of UK stock returns are statistically significant in explaining current US stock returns.

The VECM is further used to examine the price discovery process between UK and US stock markets. Price discovery implies that variables under consideration contain useful information that makes one market to lead another. In other words, whether the UK market responds to new information quickly than the US market or vice versa. The Gonzalo and Granger (1995) measure of price discovery is given as;

$$\text{GG} = \frac{\delta_{US}}{\delta_{US} - \delta_{UK}} \qquad (2.16)$$

where, δ_{UK} and δ_{US} are expected to be negative and positive, respectively. If both coefficients are significantly different from zero, with correct signs and the GG measure is equal to 0.5, then both markets contribute to price discovery at the same level. If GG = 0, only the UK market contributes to price discovery and if GG = 1, only the US market contribute to price discovery. If the GG measure is close to 1 then US market dominates in price discovery while if close to zero, the UK market dominates in price discovery.

Furthermore, the impulse response relationship is examined because Granger causality cannot detect the whole interaction between the variables in the system. The impacts of US stock returns on UK stock returns and vice-versa are investigated by orthogonalised impulse response function (OIRF). The OIRF measures the effect of a shock to an endogenous variable on itself or on another variable (see Lütkepohl, 2005). The orthogonalised innovations, denoted by ε_t, are obtained by modifying the error terms in equations (2.14) and (2.15). That is, ε_t = qu_t, such that *q Ω q' = I*, where q is any lower triangular matrix, *I* is an identify matrix, and Ω is the covariance matrices of the residuals, u_t. The orthogonalised innovations ε_t = qu_t, then satisfy E($u_s u_t'$) = *I*.

The OIRF has been criticised for being sensitive to variables ordering. Also, important variables are omitted which may lead to major distortions in OIRF. However, all omitted variables are assumed to be in the innovations and can still make the model useful for prediction.

2.3.3 *Multivariate GARCH Models – Bivariate Asymmetric BEKK and DCC models*

To examine the volatility transmission effects and capture the correlation dynamics between the two stock markets, we make use of the asymmetric BEKK GARCH model (ASY BEKK) proposed by Kroner and Ng (1998).[35] The model guarantees positive semi-definiteness by working with quadratic forms which thereby give it an advantage over the VECH models. This model permits the investigation of asymmetric responses of conditional variances and correlations to positive and negative news. The asymmetric reaction of volatility to bad and good news is being incorporated to capture the leverage effect.

The two-asset one-lag ASY BEKK model is specified as;

$$H_t = CC' + A'\,\varepsilon_{t-1}\varepsilon_{t-1}'\mathrm{A} + B'H_{t-1}B + D'\eta_{t-1}\eta_{t-1}'D \quad (2.17)$$

where *A*, *B*, *C* and *D* are all (*2 x 2*) parameter matrices. The conditional variance-covariance model (H_t) for the two-variable case can be further extended as follows;

$$h_{11,t} = c_{11} + \left(\alpha_{11}^2\varepsilon_{11,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1}\right) + \left(\delta_{11}^2\eta_{11,t-1}^2 + 2\delta_{11}\delta_{21}\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}^2\eta_{22,t-1}^2\right) \quad (2.18)$$

$$h_{22,t} = c_{22} + \left(\alpha_{12}^2\varepsilon_{11,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{22}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1}\right) + \left(\delta_{12}^2\eta_{11,t-1}^2 + 2\delta_{12}\delta_{22}\eta_{11,t-1}\eta_{22,t-1} + \delta_{22}^2\eta_{22,t-1}^2\right) \quad (2.19)$$

[35] The multivariate generalised autoregressive conditional heteroscedasticity (MGARCH) model explained include the asymmetric BEKK (Baba, Engle, Kraft and Kroner) model; dynamic conditional correlation (DCC) model. Other models include the diagonal VECH model proposed by Bollerslev, Engle and Wooldridge (1988), BEKK model proposed by Engle and Kroner (1995).

$$h_{12,t} = c_{12} + \left(\alpha_{11}\alpha_{12}\varepsilon_{11,t-1}^2 + (\alpha_{21}\alpha_{12} + \alpha_{11}\alpha_{22})\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}\alpha_{11}\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}\beta_{12}h_{11,t-1} + (\beta_{21}\beta_{12}+\beta_{11}\beta_{22})h_{12,t-1} + \beta_{21}\beta_{22}h_{22,t-1}\right) + \left(\delta_{12}\delta_{22}\eta_{11,t-1}^2 + (\delta_{21}\delta_{12} + \delta_{11}\delta_{22})\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}\delta_{22}\eta_{22,t-1}^2\right) \quad (2.20)$$

where $h_{ii,t}$ and $h_{jj,t}$ are conditional variances at time *t* of the stock return of country *i* and *j*, respectively; $h_{ij,t}$ indicates the conditional covariance between the stock returns of country *i* and country *j* at time *t*; ε_{t-1} is the vectors of errors from previous period; η_{t-1} is the vector of the asymmetric effects from previous period. The diagonal parameters in matrices *A* and *B* measure the effects of own past shocks and past volatility of market *i* on its conditional variance, while the diagonal parameters in matrix *D* measure the response of market *i* to its own past negative shocks. The off-diagonal parameters in matrices *A* and *B* capture the cross-market shock and volatility effects, while the off-diagonal elements for *D* measure the response of market *i* to the negative shocks of market *j*, which represents the cross-market asymmetric effects.[36] Regardless of the sign of element in matrix *D*, the volatilities tend to rise following a negative return shock. Since the elementary parameters governing equations (2.18) and (2.19) contain non-linear function, we use the delta method to evaluate the statistical significance of the coefficients attached to own-market shocks, cross-market shocks, own-market variances, cross-market variances, own-asymmetric effects and cross-asymmetric effects.[37]

Furthermore, the volatility of financial variables is measured using univariate GARCH model proposed by Bollerslev (1986), while the correlation between macroeconomic variables is estimated based on bivariate dynamic conditional correlation (DCC) model proposed by Engle (2002).

The GARCH *(1,1)* model uses optimal exponential weighting of historical returns to derive a volatility forecast. The parameter of the model is estimated by maximum likelihood. The conditional distribution of the GARCH model is assumed to follow normal distribution.

The conditional mean is given as;

[36] The diagonal elements in matrix *A* capture the own ARCH effect (own-market shock); the diagonal elements in matrix *B* capture the own GARCH effect (own-market volatility); and the diagonal elements in matrix *D* capture the own asymmetric effect The non-diagonal elements in matrix A capture the cross ARCH effect (cross-market shock or shock spillover); the non-diagonal elements in matrix B capture the cross GARCH effect (cross-market volatility or volatility spillover); the diagonal elements in matrix *D* capture the cross-market asymmetric effect. *D* captures the magnitude of asymmetry of volatility effect such that the term η_{t-1} takes the value *1* for negative shocks and *0* otherwise (that is, η_{t-1}= 1 when ε_{t-1}< 0 and η_{t-1}= 0 when $\varepsilon_{t-1} \geq 0$).

[37] This approximation involve the use of a Taylor series expansion and the model is an appropriate tool to detect the presence of spillover effects between the two markets.

$$r_{\mathrm{p}} = \mu + \varepsilon_{\mathrm{t}}, \quad = \varepsilon_{\mathrm{t}} = \sigma_{\mathrm{t}}\mu_{\mathrm{t}},\ \mu_{\mathrm{t}}|\Omega_{\mathrm{t-1}} \sim N(0,1) \tag{2.21}$$

The conditional variance is assumed to follow the GARCH (*1,1*) model;

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \quad \varepsilon_{\mathrm{t}} \sim N(0, H_t) \tag{2.22}$$

The conditional variance of the shocks is time-varying and is given as;

$$H_t = D_t R_t D_t \tag{2.23}$$

where D_t is an *n x n* diagonal matrix with the time-varying standard deviation from univariate GARCH models on the diagonal; R_t is the time-varying symmetric conditional correlation matrix.

Furthermore, the exponential smoothing of the correlation in the DCC model is given by,

$$q_{ij,t} = \bar{\rho}_{ij}(1 - \lambda_1 - \lambda_2) + \lambda_1\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \lambda_2 q_{ij,t-1,} \qquad i,j = 1,2 \tag{2.24}$$

where $q_{ij,t}$ is the *n x n* time-varying covariance matrix of ε_t; $\bar{\rho}_{12}$ is the time-invariant variance-covariance matrix (unconditional correlations) between the standardized residuals, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$; α is the innovation coefficient and the decaying coefficient is given by β. The λ_1 and λ_2 are parameters that govern the dynamics of conditional quasi-correlations, and they are non-negative that must satisfy $0 \leq \lambda_1 + \lambda_2 < 1$.

Finally, the conditional variances and covariances obtained from ASY BEKK and DCC models can then be used to compute the time-varying conditional correlations according to the formula expressed as;

$$\rho_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t} \cdot h_{22,t}}} \tag{2.25}$$

where, $\rho_{12,t}$ is the estimated time-varying conditional correlation coefficients between UK and US stock markets/macroeconomic data. $h_{11,t}$ and $h_{22,t}$ are the conditional variances for UK and US stock markets/macroeconomic data, respectively. The conditional covariance between UK and US is denoted as $h_{12,t}$. The conditional correlations better capture the time-varying process of international market linkages. To allow for a fat-tailed exhibited in financial time series, the maximum likelihood method is employed to estimate the parameters of the student-*t* ASY BEKK model.

2.3.4 *Volatility Impulse Response Function*

Hafner and Herwatz (2006) propose the volatility impulse response function (VIRF) as a mechanism for tracing the impact of independent shocks on volatility while avoiding usual orthogonalisation and ordering problems.[38] The BEKK model can be specified through the VECH representation proposed by Bollerslev *et al.* (1988) as;

$$vech(H_{f,t}) = vech(C) + A^* vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B^* vech(H_{t-1}) \tag{2.26}$$

The VIRF is calculated as the responses to a complete vector of shocks. Hafner and Herwatz (2006) define the VIRF as the expectation of volatility conditional on an initial shock and history, subtracted by the baseline expectation that only conditions on history. The VIRF, $V_t(Z_0)$ is defined as follows;

$$V_t(Z_0) = E[vech(H_t)|Z_0,\mathcal{F}_{t-1}] - E[vech(H_t)|,\mathcal{F}_{t-1}] \tag{2.27}$$

where Z_0 is an initial specific shock that occurred at time *0* estimated from the independent shocks $Z_t = H_t^{-1/2}\varepsilon_t$.[39] $\mathcal{F}_{t-1}$ is the observed history up to time $t-1$. The one-step ahead VIRF can be computed recursively based on the following relations;

$$V_t(Z_0) = A^*\left\{vech\left(H_0^{\frac{1}{2}}Z_0Z_0'H_0^{\frac{1}{2}}\right) - vech(H_0)\right\} \tag{2.28}$$

$$V_t(Z_0) = (A+B) * V_{t-1}(Z_0),\ t > 1 \tag{2.29}$$

where H_0 is the conditional variance-covariance matrix at time *0*. The persistence of volatility shocks depends on the eigenvalues of the matrix $A + B$. The closer the eigenvalues are to unity, the greater would be the persistence of shocks.

In comparison with the traditional Choleski decomposition impulse response function analysis of the conditional mean of the linear systems, the VIRF has the following unique properties;

1. In contrast to the traditional IRF in the conditional mean, which is an odd function of the initial shock, the VIRF is a symmetric function of the shock, that is $V_t(Z_0) = V_t(-Z_0)$.
2. In the traditional analysis, shock linearity holds such that $IRF(k * Z_0) = k * IRF(Z_0)$ while such property do not exist in equation (2.27) and as a result the VIRFs are not homogenous functions of any degree.

[38] Unlike the generalised impulse response function proposed by Koop *et al.* (2006) that examined shock through the conditional mean (the first moment), the VIRF look at the conditional variance (the second moment).
[39] Under the hypothesis of a non-Gaussian distribution, Hafner and Herwatz (2006) show that is distinctively defined, which may be treated as shocks from the past that could affect each of the markets in the future.

3. In contrast to the independence of the impulse response functions on the history of the process as in the case of the traditional analysis, the VIRF is dependent on history through the volatility state H_0 at the time when the initial shock occurs.
4. The decay in persistence of shocks is measured by the moving average matrices, ϕ_t= $(A + B)^{t-1}$A, which is comparable to the traditional analysis.

Following Hafner and Herwatz (2006), we consider four historical shocks, namely, the 1987 stock market crash, the 2001 September terrorist attack, the 2003 Iraq invasion and the 2008 stock market crash in our empirical exercise.[40] These episodes will explain the effect of an observed historical shock given the observed stock volatility at the date the shock occurs.

2.3.5 *Mixed Data Sampling Approach*

The concluding part of the empirical analysis involves the identification of macroeconomic fundamentals, financial indicators, and political, economic and financial episodes that explains the dynamic integration between UK and US stock markets. The challenge faced by researchers is how to analyse relationship between high frequency data (daily asset prices) and low frequency data (monthly, quarterly and yearly macroeconomic variables). However, the problems of mixed sampling frequencies have been commonly solved by either averaging the higher-frequency data to match the sampling rate of the lower-frequency data or adding individual components of the higher-frequency data to the regression. The first approach referred to as *time averaging* is criticised for applying equal weight to each value in the sum and further ignore any information about the timing of innovations to higher-frequency data. The second approach referred to as *step weighting* has been criticised for estimating a potentially large number of parameters (see Armesto *et al.,* 2010). Given these apparent criticisms, mixed data sampling (MIDAS) methodology solves the parameter proliferation problem while maintaining some timing information. This approach is flexible to implement regression analysis with mixed-frequency data.

MIDAS approach is a methodology developed by Ghysels *et al.* (2005, 2006). The fundamental objective of this model is that it incorporates the information in the higher frequency data into the lower frequency regression in a parsimonious, yet flexible fashion. In other words, MIDAS regression involves processes sampled at different frequencies. In this chapter, we use the Almon lag weighting (also referred to as polynomial distributed lag weighting) specification

[40] They consider in their empirical study two historical episodes; first, the "Black Wednesday", signifying the date the lira and the pound lest the ERM; second, the date the European community expand the bands of the ERM.

proposed by Ghysels *et al.* (2005, 2007). The Almon lag weighting is used to place restrictions on lag coefficients in autoregressive models. It is important to note that the number of coefficients to be estimated depends on the polynomial order and not the number of high frequency lags (Eviews 9.5 User's Guide, 2016).

The regression coefficients are modelled as a p dimensional lag polynomial in the MIDAS parameters θ for each frequency lag up to k and is expressed as;

$$y_t = X_t'\beta + \sum_{i=0}^{p} Z_{i,t}'\,\theta_i + \varepsilon_t \qquad (2.30)$$

$$Z_{i,t} = \sum_{\tau=0}^{k-1} \tau^i X_{(t-\tau)/S}^H \qquad (2.31)$$

where y_t is the dependent variable sampled at daily frequency at date t; β and θ represent the vectors of parameters to be estimated; $Z_{i,t}$ represents the constructed variables that show the distinct coefficient associated with each of the Almon polynomial order p; $X_{(t-\tau)}^H$ is the explanatory variable sampled at monthly frequency; S is high frequency regressors and the chosen number of lags k may be less or greater than S.

It follows that we use the MIDAS regression approach to investigate the determinants of stock market integration. This approach therefore helps us to accurately capture the relationship between the daily conditional correlation between US and UK markets, and the monthly macroeconomic and financial variables. Another advantage of this model is that it increases the estimation efficiency compare to simple regression models.

The variables used for our analysis are identified as follows;

(i) conditional correlation of daily stock returns as the dependent variable, (ii) conditional correlation of monthly industrial production growth, (iii) conditional correlation of monthly bond yield spread (iv) conditional correlation of monthly CPI inflation, (v) conditional volatility of monthly real exchange rate, (vi) conditional volatility of monthly gold price, (vii) conditional volatility of oil price.

The dummy variables included in this model are to measure the qualitative characteristics of the dynamics of stock market integration. The dummy variable is equal to one during economic and political events and zero otherwise. The economic and political episodes identified include;

(viii) UK and US economic recessions[41] (ix) World War II (September 1939 – April 1942), (x) Korean War (June 1950 – July 1957), (xi) Vietnam War (March 1959 – April 1974), (xii) Iraq-

[41] The dummies for UK and US recessions are measured by taking the average impact of sequence of recessions.

Kuwait War (August 1990 – February 1991), (xiii) September 11 attack and Afghanistan War (September 2001 – December 2013), (xiv) Iraq War (March 2003 – December 2011), (xv) oil price shock (October 1973 - March 1974), (xvi) October 1987 crash (September 1987 – November 1987), (xvii) European Monetary System (EMS) crisis (September 1992 – August 1993), (xviii) Mexican crisis or Tequila crisis (December 1994 – November 1995), (xix) Asian and Russian crisis (June 1997 – October 1998), (xx) dot-com bubble (March 1997 – December 1998*)*; Dot-com bust (March 2000 – September 2002), (xxi) US housing bubbles (January 2005 – May 2007*),* (xxii) sub-prime mortgage crisis and global financial crisis (August 2007 – June 2009), (xxiii) period of UK and US quantitative easing (QE) program;[42] (xxiv) Eurozone debt crisis (May 2010 – June 2015).

In summary, the potential drivers of stock market integration process are underpinned by the changes in market conditions. It is expected that stock market integration should increase over time as the macroeconomic variables that influence stock prices converge. Similarly, we expect increases in integration over time as financial variables that influence stock prices become less volatile. We further expect that period of crisis should increase stock market integration while period of tranquillity should reduce stock market integration.

[42] The QE timeline for UK include; BoE announces £75 billion QE program on March 5, 2009; BoE expands program to £125 billion on May 7, 2009; BoE extends program to £175 billion on August 6, 2009; BoE enlarges program to £200 billion on November 5, 2009; BoE expands program to £275 billion on October 6, 2011; BoE increases program to £325 billion on February 2012; BoE expands program to £375 billion on July 5, 2012. The QE timeline for US include; Fed announces $500 billion QE program on November 25, 2008; Fed will purchase additional $600 billion in Treasuries on November 3, 2010; Fed expands program with additional $400 billion on September 21, 2011; Fed extends purchases of long bonds/sales of short bonds on June 20, 2012; Fed expands program with another $40 billion on September 13, 2012; Fed continue to purchase $45 billion in long term treasuries per month on December 12, 2012.

2.4 Dataset

The dataset used consists of daily series of FT30 and Dow30 indices from 1st July 1935 to 30th June 2015. The dataset is obtained from the Financial Times and DataStream.[43] The sample comprises of 20,804 observations for each stock market index. The monthly macro and financial data are obtained and verified from various sources such as the Federal Reserve Bank of St. Louis, OECD and NBER (see data appendix).

The descriptive statistics of the daily stock returns (i.e. logged first differences) are presented in Table 2.3. The test for the null hypothesis of the presence of unit root with (ADF and PP tests) and without structural breaks (Zivot and Andrews test) on the price level cannot be rejected but they are stationary at the first difference.[44] The average returns are positive and statistically significant in the full period and periods 2 and 4. The UK market has over the years been more volatile than the US market. The estimated coefficient of standard deviation of 1.00% exceeds slightly the US (0.09%).

The kurtosis values for the returns are greater than three implying leptokurtic distributions (that is, fat-tailed distributions), extreme observations and possibly volatility clustering. The higher kurtosis values in the return series suggest that large shocks are quite common. In the full sample, there are larger shocks in the US market than in the UK. The skewness values imply a degree of asymmetry (negative or positive shocks). There is strong evidence that negative shocks (full period and periods 1, 2, 4, 5 and 6) are more prevalent than positive shocks (sub-period 3). Furthermore, the Jarque-Bera (JB) test for normality indicates that we reject the null that the stock returns are normally distributed for all the periods. The problem of non-normality may be caused by the existence of outliers over the period of sample, which stems from infrequent exogenous shocks (such as political conflict, terrorist attacks, macroeconomic shocks, financial crises etc.) instead of normal progression of the economic data. The Ljung-Box test statistics find significant presence of serial correlation in the returns for all the periods. The serial correlation for the squared returns, which is a proxy for volatility, suggests a strong evidence of presence of high persistence, time-varying volatility and volatility clustering. The McLeod-Li test indicates strong ARCH effects or conditional heteroscedasticity in all returns.

[43] The stock data we used are actual stock prices unlike the UK stock returns obtained by Engsted and Tanggard (2004) which was constructed using the de Zoete and Wedd value-weighted Equity Price Index and associated dividends.
[44] The results of the unit root tests are available upon request.

Table 2.3 further shows the test for equality of means, variances, medians and distributions between the periods. The two-sample test for equality of means do not find significant difference in the means between the sub-periods of UK and US markets. However, the test on the equality of standard deviations (variances) reject the null hypothesis of equality of variance between the periods of the stock markets. The Kolmogorov-Smirnov equality of distributions tests reject the null hypothesis that there is no difference in distributions between the subsamples. The median test rejects the null hypothesis that there is no difference in median between periods 1 and 2, periods 2 and 3, and periods 3 and 4, while it fails to reject the null hypothesis between periods 4 and 5 and periods 5 and 6. This suggests that the first half of the sample period comes from population with the same median. Since our analysis focuses more on the second moment, we are justified in carrying out a subsample analysis on the basis of the differences in equality of volatility and distribution between the subsamples.

Figure 2.7 depicts the plots of the UK and US stock returns for the subsamples. Invariably, the UK market shares similar phases of market dynamics with the US market. The period of interwar/Second World War shows the US stock returns fluctuating more intensely than the UK while UK stock returns fluctuates more rapidly than the US in the pre-UK exchange control period. This suggests significant divergent in stock returns of UK and US in these periods may affect the degree of stock market integration. The significant spikes in the post-UK exchange controls and post-EMU periods are attributed to the 1987 stock market crash and 2008 global financial crisis, respectively. The monumental shifts in the stock returns of these markets due to severe shocks are worthy of further empirical investigation. Overall, the plots show the clustering of larger returns around major historical episodes, indicating the presence of heteroskedasticity.

Figure 2.8 demonstrates the histogram and kernel density estimation of the stock returns of UK and US markets. The density estimate shows sharp declining slope both side and the bulk of density are located in the centre with two thin longer tails either side. The densities follow generally the same pattern as the histograms predicted, albeit some have higher and sharper peaks. In the full period, the densities of UK and US have higher and sharper peaks than the histogram exhibit. In some sub-periods, particularly for UK market, the Kernel estimate shows how the histogram can miss out on some attributes of the density. In period 3, both US and UK estimates have a more normal bell-shape. Apart from period 3, the estimates show a skewed, sharper peaks and a long tail extending to the left. This is an attribute that leads to excess kurtosis.

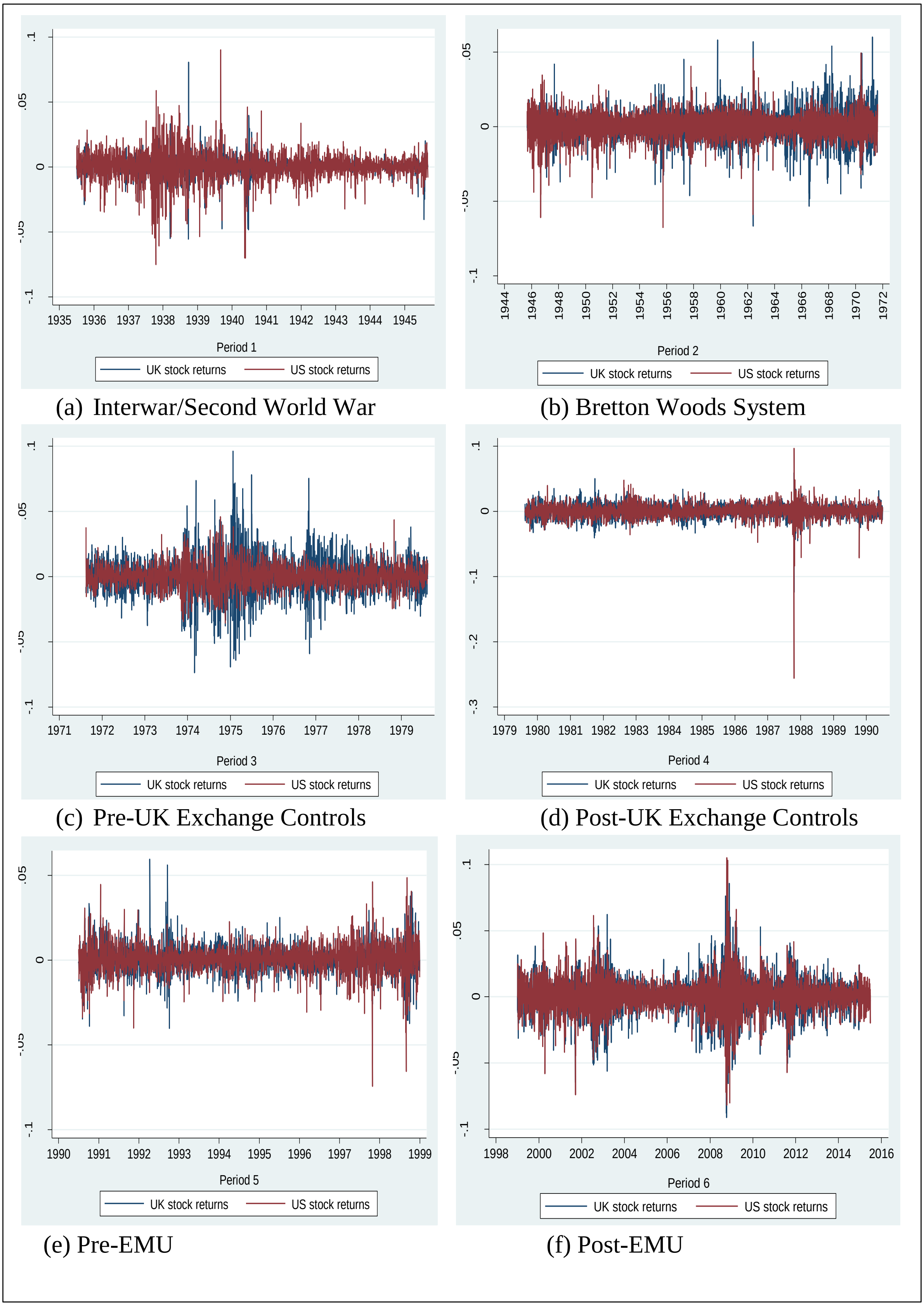
In summary, the descriptive statistical evidence of higher order serial correlation, non-normality, conditional heteroskedasticity and volatility clustering support the decision to model the stock return volatility dynamics and transmission process between UK and US through a GARCH-type process. The use of GARCH family models to analyse the stock return dynamics will be particularly useful for market practitioners and policymakers.

Table 2.3: Descriptive Statistics of UK and US Stock Returns

Obs	Mean	Std Dev	Skw.	Kurtosis	JB test	Q (12)	Q^2 (12)	ARCH (4) effect
Full 1935-2015								
UK	0.000**	0.010	-0.201***	11.23***	3363***	235.7***	13276***	3441***
US	0.000***	0.009	-1.112***	35.06***	8911***	60.34***	2230***	922.0***
Period 1 1935-1945								
UK	0.000	0.007	-0.322***	21.49***	680.7***	305.2***	897.6***	469.7***
US	0.000	0.011	-0.493***	10.37***	487.4***	36.17***	725.9***	184.9***
Period 2 1945-1971								
UK	0.000**	0.008	-0.135***	10.82***	1034***	314.7***	581.4***	207.7***
US	0.000***	0.007	-0.523***	9.093***	1135***	135.0***	1105***	461.8***
Period 3 1971-1979								
UK	0.000	0.016	0.255***	6.117***	184.2***	46.94***	1596***	345.9***
US	-0.000	0.009	0.253***	4.655***	104.5***	90.36***	773.5***	188.8***
Period 4 1979-1990								
UK	0.001**	0.011	-1.062***	14.01***	887.3***	27.39***	1268***	785.6***
US	0.001**	0.011	-4.341***	106.8***	2886***	17.36	129.8***	78.29***
Period 5 1990-1999								
UK	0.001***	0.009	0.170***	6.502***	196.9***	57.96***	579.7**	135.9***
US	0.000	0.009	-0.495***	9.683***	391.6***	35.29***	350.4***	138.2***
Period 6 1999-2015								
UK	-0.000	0.013	-0.276	7.985***	528.8***	53.82***	3075***	696.8***
US	0.000	0.011	-0.063*	11.19***	675.5***	54.61***	3823***	715.9***

	Equality of mean Two sample t-test ($*10^{-3}$)	Equality of Std. Dev. Levine test	Equality of distributions Kolmogorov-Smirnov test	Equality of median
UK: Period 1 – period 2	0.145 (0.836)	0.008 (1.259***)	0.071***	8.601***
US: Period 1 – period 2	0.231 (0.903)	0.008 (0.416***)	0.066***	0.064
UK: Period 2 – Period 3	-0.004 (-0.012)	0.010 (4.394***)	0.197***	3.026*
US: Period 2 – Period 3	-0.254 (-0.998)	0.008 (1.736***)	0.104***	9.012***
UK: Period 3 – Period 4	0.457 (1.082)	0.013 (0.469***)	0.087***	13.11***
US: Period 3 – Period 4	0.438 (1.368)	0.010 (1.449***)	0.041**	5.729**
UK: Period 4 – Period 5	-0.222 (-0.723)	0.009 (0.656***)	0.072***	2.038
US: Period 4 – Period 5	0.105 (0.339)	0.010 (0.598***)	0.049***	0.144
UK: Period 5 – Period 6	-0.339 (-1.110)	0.011 (2.084***)	0.064***	0.383
US: Period 5 – Period 6	-0.346 (-1.184)	0.011 (1.793***)	0.062***	0.283

Notes: '*', '**' and '***' denote significant levels at 10%, 5% and 1%. The Ljung-Box (Q) applied to raw and squared returns to test for serial correlation and heteroskedasticity using *12* lags. The skewness, kurtosis and Jarque-Bera tests are used to test for asymmetry, fat tail and normal distribution. McLeod and Li (1983) test is used to test for ARCH effects. The two-sample tests perform test on the equality of means. The Levine test performs test on the equality of standard deviations. The test statistic for the two-sample and Levine tests are reported in parenthesis. The Kolmogorov-Smirnov test perform the test of the equality of distributions. A non-parametric test on the equality of medians test the null hypothesis that the *k* samples were drawn from populations with the same median. The chi-squared test statistic is computed for two samples.



(a) Interwar/Second World War

(b) Bretton Woods System

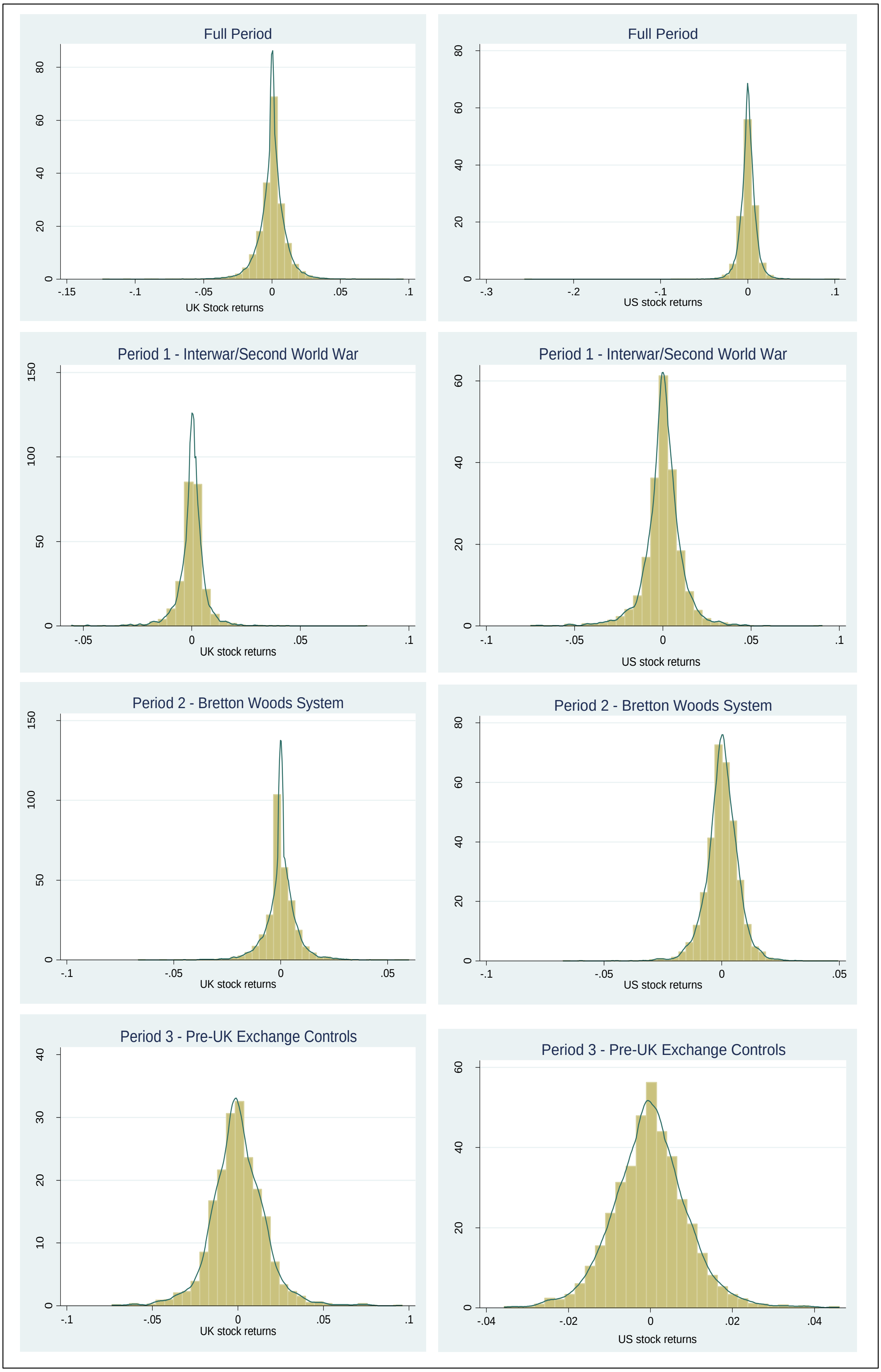
(c) Pre-UK Exchange Controls

(d) Post-UK Exchange Controls

(e) Pre-EMU

(f) Post-EMU

Figure 2.7: Dynamics of UK and US Daily Stock Returns



Full Period
0
20
40
60
80
-.15
-.1
-.05
0
.05
.1
UK Stock returns
Full Period
0
20
40
60
80
-.3
-.2
-.1
0
.1
US stock returns
Period 1 - Interwar/Second World War
0
50
100
150
-.05
0
.05
.1
UK stock returns
Period 1 - Interwar/Second World War
0
20
40
60
-.1
-.05
0
.05
.1
US stock returns
Period 2 - Bretton Woods System
0
50
100
150
-.1
-.05
0
.05
UK stock returns
Period 2 - Bretton Woods System
0
20
40
60
80
-.1
-.05
0
.05
US stock returns
Period 3 - Pre-UK Exchange Controls
0
10
20
30
40
-.1
-.05
0
.05
.1
UK stock returns
Period 3 - Pre-UK Exchange Controls
0
20
40
60
-.04
-.02
0
.02
.04
US stock returns

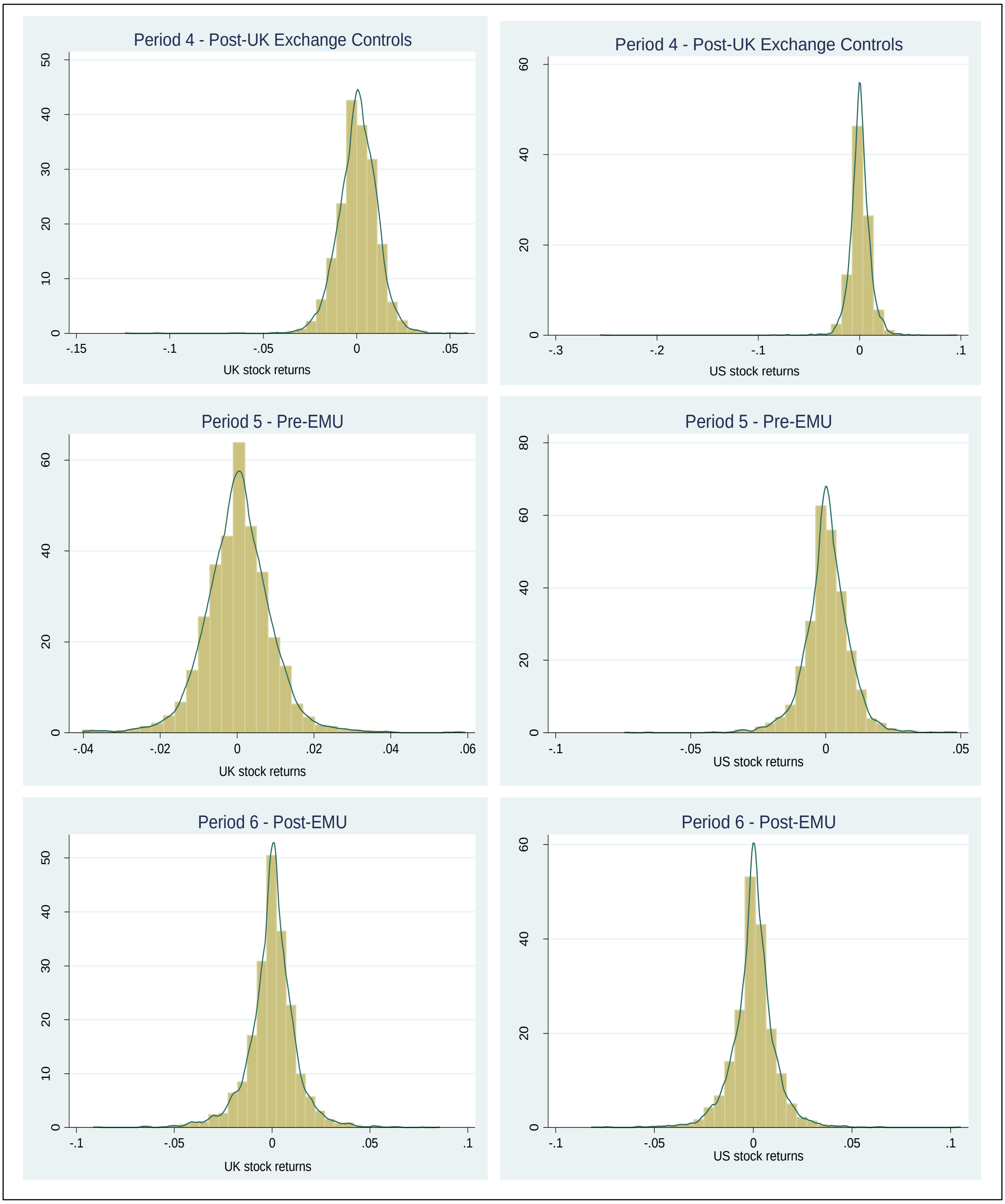


Figure 2.8: Kernel Estimate of Daily Stock Returns for UK and US Markets

2.5 Empirical Results and Discussions

The empirical results for cointegration relationships, impulse responses, spillover effects and time-varying conditional correlations are explained in this session. In section 2.5.1, we present the empirical evidence on long-run and short-run relationships between UK and US stock markets. Section 2.5.2 reports the impulse response of shocks to stock returns of both markets. The findings on the nature of spillovers and volatility impulse response function are reported in session 2.5.3. We show the time-varying condition correlation between the markets in section 2.5.4. Finally, we report the determinants of stock market integration in section 2.5.5.

2.5.1 Co-integration Relationships

The use of various cointegration tests will show robustly the existence of cointegration relationship between our understudy markets. Table 2.4 sets out the results for the cointegration analysis using the log prices of UK and US stock indices. The Akaike information criteria (AIC) was used to select the maximum optimal lags for this analysis.[45] To start with, the Engle-Granger residual based tests indicate that there is no long run equilibrium between the UK and US stock markets for the full sample and subsamples. Similarly, the Johansen tests which incorporate both a linear trend and a constant, show that no cointegrating vectors were identified in all the periods under consideration, which therefore suggest that the markets are not integrated in the long-run. In other words, the null hypothesis that UK and US stock markets are not cointegrated ($r = 0$) against the alternative of one cointegrating vector ($r \leq 1$) cannot be rejected, since both the λ_{trace} and λ_{max} statistics are below the critical values at 1% and 5% levels. This suggests that the Johansen and Engle-Granger cointegration tests consistently establish the case of no cointegration relationship between the two markets.

However, based on the cointegration regression models (FMOLS and CCR), long-run equilibria exist during periods of interwar/WW2, BWS, post-UK EC and Post-EMU. In addition, the FMOLS and CCR tests show strong long-run relationship between UK and US in the full period with an estimated value of 0.635 and 0.774, respectively. Furthermore, when we control for structural breaks in the cointegrating relationships by using the Gregory-Hansen test (GH), we find long-run equilibria during periods of pre-UK EC, post-UK EC and post-EMU. This suggests that the markets co-move towards a stationary long-run equilibrium path in these periods. The results of FMOLS, CCR and GH models have so far shown consistency of long-run relationships during periods of post-UK EC and post-EMU.

[45] The Bayesian Information Criteria (BIC) gave similar lag lengths.

If we based the results on Engle-Granger methodology and Johansen technique, our findings will be consistent with Taylor and Tonks' (1989) evidence of non-existence of cointegration between UK and US for post-UK EC period. Apparently, the use of other cointegration tests establishes long-run relationship during the post-UK EC period. The results are justified on the basis that these periods witnessed the most drastic financial reforms, leading to increased liberalisation and globalisation of the financial system. This further implies that less market segmentation after the abolition of all forms of exchange and capital controls in 1979 leads to cointegration relationship between UK and US stock markets. With the combination of the results of the cointegration analysis, we conclude that the two markets are cointegrated in both the full period and sub-periods. The long-run relationship between UK and US is further supported by the evidence of cointegrated mature markets provided by Floros (2005) and Hatemi (2008).

In addition, the structural breakpoints captured by GH regime shift test in the various sub-periods can be linked to historical political and economic episodes. The breakpoint of May 1941 in the Interwar/WW2 period was as a result of economic devastation caused by the Second World War in Europe and the outbreak of war in the Pacific. The breakpoint of July 1949 in the BWS period marked the end of the post-war slump and the beginning of rapid economic recovery in Europe and Japan. The breakpoint of April 1977 in the pre-UK EC period was due to the inflationary pressure and high unemployment in both economies. The breakpoint of January 1984 in post-UK EC period can be traced to the introduction of economic policies in tackling rising inflation and critical macroeconomic distortions. The breakpoint of October 1992 in the pre-EMU period can be linked to the forced withdrawal of the British pound sterling from the Exchange Rate Mechanism (ERM) leading to the European currency crisis of 1992/1993. In post-EMU period, the breakpoint of April 2005 was a signal that the housing bubble could bust given the increasing foreclosure rates in the US. Overall, the crisis episodes are plausible sources of structural breaks in global stock market integration.

We would however be cautious in interpreting the long-run relationship as a sign of integration due to the fact that volatility spillover and market contagion can also be attributed to their long-run equilibrium. For example, the influence of market contagion is more likely given the occurrence of episodes such as 1973/1974 global oil crisis during pre-UK EC period, 1987 stock market crash during post-UK EC period and 2008 stock market crash in post-EMU. Another implication from the cointegration relationship between the two markets is the existence of arbitrage opportunities which enhances the price discovery aspect of financial markets.

In summary, the results do not show evidence of consistent long-run relationships based on the application of different cointegration methodologies. However, we conclude that though the two markets may exhibit deviations from each other in the short run, they still will co-move in the long-run. This therefore suggests that if the stock markets have long run comovement, then the examination of volatility spillover, time-varying conditional correlation and market contagion is imperative. Our conclusion is based on the fact that the FMOLS and CCR make a clear distinction between the endogenous (i.e. UK market) and exogenous (i.e. US market) variables. In the next session, we further examine the return spillovers between these markets using the VECM and measure of price discovery.

Table 2.4: Cointegration Relationships between UK and US Stock Prices

Cointegration tests	**Full Period 1935-2015 (5 lags)**	**Interwar/WW2 1939-1945 (4 lags)**	**BWS 1945 – 1971 (4 lags)**	**Pre-UK EC 1971 – 1979 (3 lags)**	**Post-UK EC 1979 – 1990 (3 lags)**	**Pre-EMU 1990 – 1999 (2 lags)**	**Post-EMU 1999 – 2015 (6 lags)**
Engle-Granger Test	-2.011	-1.746	-2.014	-1.382	-1.808	-2.205	-2.195
Fully Modified OLS	0.635* (0.351)	1.464*** (0.443)	0.508** (0.235)	0.547 (0.981)	0.609*** (0.201)	0.204 (0.166)	0.987*** (0.319)
Canonical Correlation Regression	0.774*** (0.085)	1.220*** (0.329)	0.748*** (0.075)	0.782 (0.939)	1.149*** (0.096)	0.548*** (0.056)	1.335** (0.517)
<u>Johansen test</u>	λ_{trace}	λ_{trace}	λ_{trace}	λ_{trace}	λ_{trace}	λ_{trace}	λ_{trace}
r = 0	6.772	9.684	12.86	7.270	8.127	9.379	6.465
r ≤ 1	0.134	2.499	2.036	2.466	0.183	0.449	1.473
	λ_{max}	λ_{max}	λ_{max}	λ_{max}	λ_{max}	λ_{max}	λ_{max}
r = 0	6.638	7.185	10.83	4.804	7.944	8.929	5.071
r ≤ 1	0.134	2.499	2.036	2.466	0.183	0.449	1.473
Gregory-Hansen Test: Break point	-47.22 Oct. 1983	-32.81 May 1941	-36.70 Jul. 1949	-68.80** Apr 1977	-104.49*** Jan 1984	-38.40 Oct 1992	-90.44*** Apr 2005

Notes: The superscripts *, ** and *** denote significant levels at 10%, 5% and 1%. We use AIC/HQIC for our optimal lag selections. The critical values for the maximum statistics (λ_{max}) for 1% and 5% are 15.41 and 20.04 and Trace statistics (λ_{trace}) are 14.07 and 18.63 based on zero co-integrating relationship. For one co-integrating relationship, their critical values are 3.76 and 6.65. The Engle-Granger residuals-based tests for the null of no co-integration with critical values at 1%, 5% and 10% equal to -3.96, -3.41 and -3.12, respectively. The critical values for Gregory-Hansen (GH) are -69.37 for 1%, -58.58% for 5% and -53.31 or 10%. Period 1 – Interwar and World War 2; Period 2 – Bretton Woods System (BWS); Period 3 – Pre-UK Exchange Controls (Pre-UK EC); Period 4 – Post-UK Exchange Controls (Post-UK EC); Period 5 – Pre-European Monetary Union (Pre-EMU); Period 6 – Post-European Monetary Union (Post-EMU).

2.5.2 Return Spillovers and Price Discovery

In view of the findings of long-run relationship between US and UK stock markets, we estimate the short-run relationship using the vector error correction model (VECM). The VECM estimates are set out in Table 2.5. The AIC selected the maximum optimal lags for the VECM on the basis that it is more parsimonious in terms of coefficients estimated. The two speed of adjustment coefficients indicate as expected that δ_{UK} is negative and significant, while δ_{US} is positive and significant, suggesting a joint error correction to restore equilibrium on the following day. The coefficients of the speed of adjustment (δ_{UK} and δ_{US}) further suggest that the UK returns are on average lower than the level predicted by the long-run equilibrium and they adjust by rising toward the US returns. By the same token, the US stock returns tend to exceed the UK returns, and therefore decrease to restore long run equilibrium.

Since we have established the existence of a long-run relationship between UK and US stock prices, the condition necessary for the use of Gregory-Gonzalo (GG) based information share measure in the analysis of the price discovery process has been satisfied. The results of the full period indicate an evidence of bidirectional return spillovers between US and UK markets. Consequently, when the two cointegrated series are in disequilibrium in the short run, it is the US stock index that makes greater adjustment in order to establish equilibrium. Since the error correction term of the US return equation is greater than that of the UK returns equation, the US market leads the UK market in price discovery by 70.3%. The Granger-causality test also confirms bidirectional causality between the two markets.

Similar bidirectional return spillovers and causality exist in all the sub-periods except the pre-EMU period. In this period, the UK market leads the US market by 3 days and not vice versa, suggesting a unidirectional return spillover and causality. However, the US market leads the UK in price discovery in all the other sub-periods. Overall, the US stock market has maintained a dominant influence over the UK stock market in terms of return spillovers and price discovery process which is in line with past studies (e.g. Kim *et al*., 2005; Syriopoulos, 2007; Singh *et al*., 2010).

We attribute our results to few possible explanations. Firstly, the US economy is the largest in the world and being a global financial centre, market participants can eliminate arbitrage opportunities more rapidly in the US than UK. Secondly, the strong degree of market efficiency in these markets suggests that based on our daily series analysis, one day is sufficiently long enough for the stock index to reflect fundamental information (e.g. macroeconomic news).

Finally, the US stock index has the potential to adjust more rapidly to reflect the fundamental value if unexpected shocks hit the financial system.

Figure 2.9 demonstrates that the cointegration relationships between UK and US stock returns change across the periods. The pre-UK exchange controls period shows the most unstable cointegration relationship while the post-UK exchange controls period displays the most stable cointegration relationship. In like manner, the post-EMU period has been less stable in cointegration relationship compare to the pre-EMU period. Meanwhile, the periods of shocks and unexpected changes (1987 October stock market crash, Asian and Russian financial crisis, high-tech bubble bust, and 2008 September stock market crash) have clear effects on the predictions from the cointegration equations.

The diagnostic statistics indicate the absence of serial correlation in the residuals for the full period and most subsamples. However, there are significant serial correlation in the squared residuals for all the periods suggesting the presence of conditional heteroscedasticity and volatility clustering. The VECM estimates satisfy the eigenvalue stability condition on the basis that the modulus of each eigenvalue is strictly less than 1 in both full samples and subsamples. After controlling for calendar effects and exogenous shocks such as 1987 stock market crash, September 11 2001 teeorist attack and 2008 stock market crash, our results did not mitigate the presence of serial correlation in other subsamples we found them. Hence, we further investigate the shock and volatility dynamics between the two markets in subsequent sessions.

Table 2.5: VECM Results

$$R_{UK,t} = \alpha_{UK} + \delta_{UK} z_{t-1} + \sum_{i=1}^{p_{UK}} \beta_{UK,i} R_{UK,t-i} + \sum_{j=1}^{q_{US}} \beta_{US,j} R_{US,t-j} + \varepsilon_{UK,t}$$

$$R_{US,t} = \alpha_{US} + \delta_{US} z_{t-1} + \sum_{j=1}^{q_{US}} \beta_{US,j} R_{US,t-j} + \sum_{i=1}^{p_{UK}} \beta_{UK,i} R_{UK,t-i} + \varepsilon_{US,t}$$

	Full Period 1935-2015		**Interwar/WW2 1939-1945**		**BWS 1945 – 1971**		**Pre-UK EC 1971 – 1979**		**Post-UK EC 1979 – 1990**		**Pre-EMU 1990 – 1999**		**Post-EMU 1999 – 2015**	
	$R_{UK,t}$	$R_{US,t}$	$R_{UK,t}$	$R_{US,t}$	$R_{UK,t}$	$R_{US,t}$	$R_{UK,t}$	$R_{US,t}$	$R_{UK,t}$	$R_{US,t}$	$R_{UK,t}$	$R_{US,t}$	$R_{UK,t}$	$R_{US,t}$
δ_{UK}	-.216*** (.018)		-.319*** (.050)		-.279*** (.022)		-.298*** (.043)		-.169*** (.029)		-.093** (.039)		-.399*** (.057)	
$\beta_{UK,1}$	-.712*** (.019)	-.489*** (.018)	-.419*** (.052)	-.673*** (.089)	-.499*** (.023)	-.372*** (.022)	-.576*** (.044)	-.330*** (.026)	-.766*** (.032)	-.437*** (.025)	-.838*** (.042)	-.401*** (.042)	-.721*** (.055)	-.776*** (.052)
$\beta_{UK,2}$	-.663*** (.019)	-.459*** (0.018)	-.279*** (.052)	-.548*** (.089)	-.436*** (.023)	-.352*** (.022)	-.550*** (.044)	-.307*** (.025)	-.635*** (.033)	-.279*** (.018)	-.752*** (.044)	-.331*** (.043)	-.708*** (.052)	-.715*** (.049)
$\beta_{UK,3}$	-.654*** (.019)	-.429*** (.018)	-.321*** (.051)	-.464*** (.089)	-.420*** (.023)	-.302*** (.022)	-.490*** (.044)	-.265*** (0.025)	-.582*** (.034)	-.164*** (.019)	-.674*** (.044)	-.311*** (.043)	-.681*** (.049)	-.634*** (.046)
δ_{US}		.511*** (.017)		.672*** (.088)		.409*** (.021)		.376*** (.025)		.527*** (.023)		.497*** (.025)		0.865*** (.055)
$\beta_{US,1}$	-.180*** (.036)	.056* (.034)	-.219*** (.053)	-.202** (.093)	-.272*** (.036)	-.169*** (.034)	-.459*** (.104)	.158*** (.060)	-0.063 (.062)	.085** (.038)	.057 (.086)	.161* (.085)	-.162* (.085)	.275*** (.080)
$\beta_{US,2}$	-.223*** (.034)	.240 (.032)	-.258*** (.052)	-.190** (.090)	-.295*** (.035)	-.224*** (.033)	-.593*** (.097)	.099* (.056)	-.168*** (.057)	.038 (.031)	.016 (.081)	.116 (.080)	-.038 (.078)	.236*** (.074)
$\beta_{US,3}$	-.185*** (0.033)	.040 (.031)	-.258*** (.051)	-.135 (.089)	-.237*** (.033)	-.169*** (.031)	-.457*** (.091)	.101* (.052)	-0.097* (0.053)	0.041* (0.022)	-.004 (.075)	.069 (.074)	.038 (.071)	.251*** (.067)
R^2	0.465	0.479	0.398	0.482	0.398	0.441	0.461	0.408	0.496	0.483	0.466	0.484	0.506	0.516
GC	127.6***	791.3***	96.20***	94.93***	84.06***	315.7***	57.38***	176.4***	82.87***	194.7***	6.780	104.7***	251.6***	41.98***
PD	0.703		0.678		0.594		0.558		0.757		0.842		0.684	
Q(6)	10.12	0.954	0.959	0.575	17.62***	1.839	9.976	1.013	21.67***	1.369	54.58***	3.453	41.47***	20.21***
$Q^2(6)$	7360***	1693***	632.0***	654.1***	468.0***	620.4***	557.0***	306.2***	793.4***	107.4***	542.2***	286.5***	1265***	1437***

Notes: The *, ** and *** denotes significant levels at 10%, 5% and 1%. The Ljung-Box test for serial correlation in the raw residuals (Q) and squared residuals (Q^2) up to 6 lags. GC represents Granger-Causality test. Price discovery (PD) is calculated as GG = $\frac{\delta_{US}}{\delta_{US} - \delta_{UK}}$ (where δ_{US} and δ_{UK} are the speed of adjustments of UK and US, respectively).

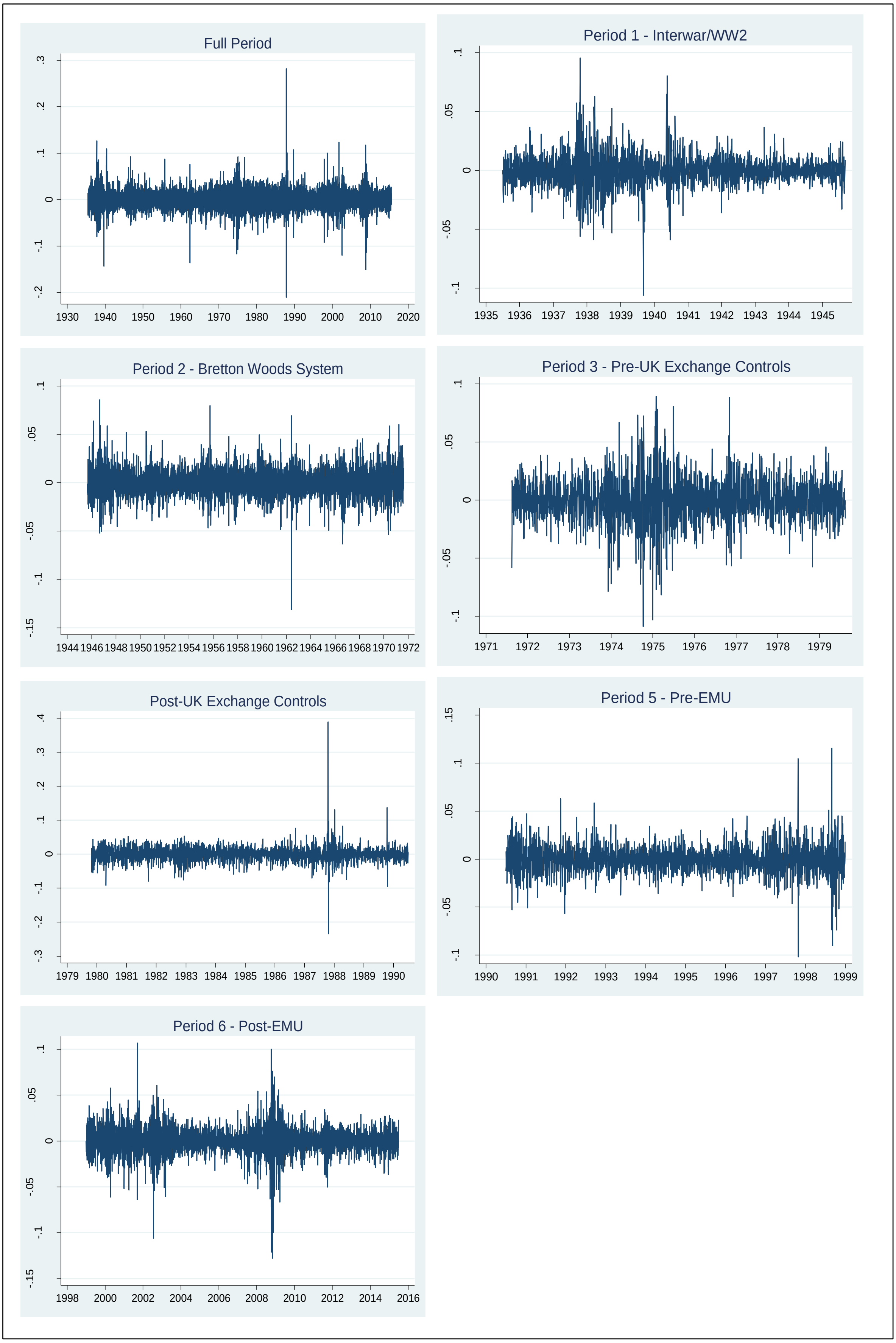


Figure 2.9: Cointegrating Relationships between UK and US Stock Returns

2.5.3 Orthogonalised Impulse Response Function

An innovation or shock to any of the understudy variables may be interpreted as arising from unanticipated financial and economic news. The orthogonalised impulse response function (OIRF) is used to measure the responsiveness of the endogenous variable in the VEC models to shocks to each of the exogenous variables.[46] Generally, shocks are transitory when the effect of innovation dies out over time and permanent if the effect of a shock shifts the system to a new equilibrium in the long-run. As a result of the first-difference stationary variable for the VEC model, the shocks appear permanent because they do not taper off to zero. Figure 2.10 and Figure 2.11 demonstrate the time path of impulse responses of each market to one standard deviation on the other market for the full samples and subsamples. The forecast horizon is measured in 20-day-ahead on the horizontal axis, whereas the vertical axis measures the magnitude of response, scaled such that 1.0 equals one standard deviation.

In the full period, the estimated OIRF converges to a positive asymptote. The shock to the stock returns in UK has a permanent effect on the stock returns in the US, and vice versa. The response of UK to the US market shocks demonstrates a cyclical pattern over a relatively protracted period of time. Its impact response is 0.04% on day-1, sharply rises to 0.06% by day-3, and continue in an oscillatory manner over the 20-day period. However, the response of US to shock originating from the UK is less oscillatory; starting from 0.25% on day-1, revolves closely around 0.05% over time. Overall, the transmission of shock from the US to UK is significantly more than the other way round.

During interwar/WW2 period, shocks transmission between UK and US are oscillatory. The response of UK market to shock from US starts at 0.02% on day-1, and suddenly jumps to 0.10% on day-2, declines to 0.03% on day-6, and continues in a cyclical way over time. In contrast, the response of US market to shocks from US begin from 0.13% in day-1, and have continue to oscillate sharply over time. In a similar fashion, BWS and pre-UK EC periods show cyclical pattern of responses to shocks between the two markets. In post-UK EC, pre-EMU and post-EMU periods, the response of US to shocks from the UK is less oscillatory and tends towards stability from day-12. Overall, the UK stock returns are more responsive to shocks originating from the US than vice-versa.

[46] The UK stock market shocks are represented by the FT30 index returns while the US stock market shocks are represented by the Dow30 index returns.

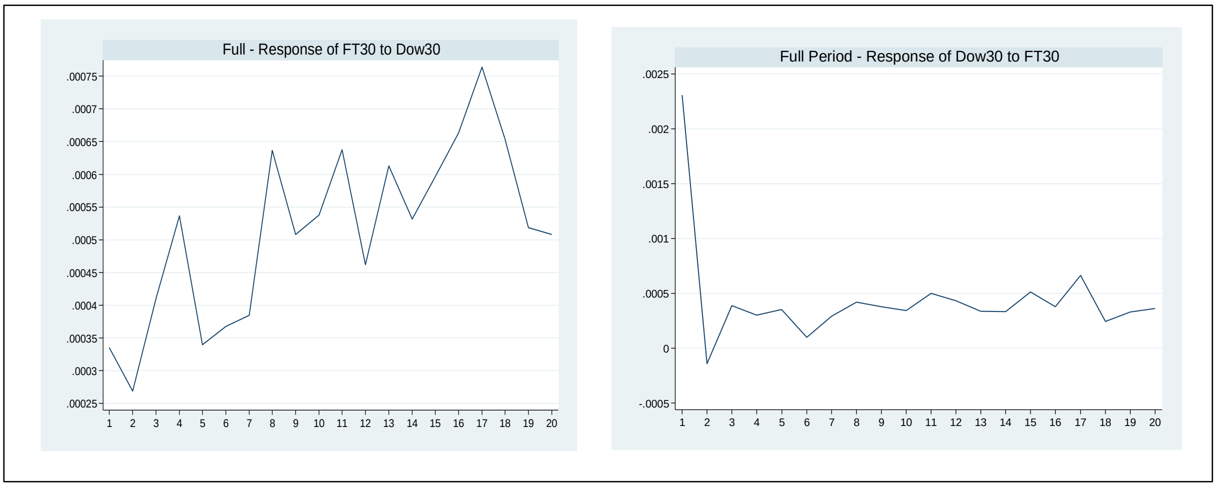


Figure 2.10: Orthogonalised Impulse Response Function - Full Sample

Figure 2.11: Orthogonalised Impulse Response Function - Subsamples

2.5.4 Shock and Volatility Spillover Effects

The spillover effects occur when the arrival of news from one market has persistent effect on another market. The ASY BEKK model allows the conditional variances and covariances of the two returns from US and UK stock markets to affect each other thereby making it possible to test the null hypothesis of no shock/volatility spillover effects in one or even both directions. The residuals ($\varepsilon_{UK,t}$, $\varepsilon_{US,t}$) obtained from the VECM models are fitted into the bivariate ASY BEKK GARCH model to investigate the volatility dynamics. As a result of the fat-tailed distribution, we estimate the model of equations (2.18) and (2.19) assuming error terms from the Student-t distribution. The assumption of student-t distribution delivers better estimation for conditional errors than assuming a normal distribution (Susmel and Engle, 1994). The statistical significance of the parameters of the model is evaluated using the Delta method. Empirical estimates for the above ASY BEKK specification are reported in Table 2.6. A considerable number of significant transmission coefficients suggest substantial interactions between the conditional volatilities. The stationarity condition for the BEKK covariance matrix H_t is satisfied as the largest eigenvalue of the sum of the Kroneker products of ARCH and GARCH terms has eigenvalue less than unity in modulus.[47] This suggests a high level of persistent shocks in both markets. The likelihood ratio (LR) test soundly rejects the null of constant covariance matrix H_t.[48] The estimated diagonal parameters are significant in all periods indicating own domestic past shocks and volatilities affect the conditional variances of the UK and US stock markets. The off-diagonal elements of the *ARCH* and *GARCH* measure the cross-market effects such as shock and volatility spillovers between the two markets.

In the full period, we find evidence of bidirectional shock spillovers between UK and US. This suggests that the impact of past shock originating from the US market increases the UK current volatility ($\varepsilon_{t-1,1}\varepsilon_{t-1,2}$ = 0.017), as does a past shock originating from UK has a decreasing effect on the US market's current volatility ($\varepsilon_{t-1,2}\varepsilon_{t-1,1}$ = -0.007). Similar bidirectional shock spillovers exist in post-EMU period, suggesting a significant linkage between the two markets. During periods of Bretton-Wood system and post-UK exchange controls, we find unidirectional shock spillover, such that past shocks from the US increase the current volatility of UK. In contrast, periods of Interwar/WW2 and pre-UK exchange controls indicate that past shocks

[47] The persistence of the whole system is captured by the eigenvalues of the system. The closer the eigenvalues to unity, the higher would be the persistence of shocks (see Panopoulou and Pantelidis, 2009).
[48] The LR statistic tests for the null (H_0: $\alpha_{11}= \alpha_{12} = \alpha_{21}= \alpha_{22}= \beta_{11}= \beta_{21}= \beta_{21}=\beta_{22} = 0$), calculates to 1114, and with the degrees of freedom being equal to 8. The null is rejected at all significant levels. Likewise, the ARCH elements in A' or the GARCH elements in B' are equal to 0 is rejected.

from US decrease the current volatility of UK. This implies that US market plays a dominant role in shock transmission as it is relatively insulated from external shocks itself. On volatility spillover, the full period shows insignificant volatility spillovers between UK and US. However, bidirectional volatility spillovers exist between the markets in post-EMU period. This suggests that the impact of past volatility originating from the US market decreases the UK current volatility ($h_{t-1,12}$ = -0.034), as does a past volatility originating from UK has an increasing effect upon the US market's current volatility ($h_{t-1,21}$ = 0.030). This is consistent with the finding of significant volatility spillover after the introduction of the euro currency by Savva *et al.* (2009). We also reckon that the increased in shock and volatility spillovers in the post-EMU period can be attributed to macroeconomic shocks and changing market conditions (2000-2002 dot-com bust, 2005-2007 housing bubble, 2007-2009 global financial crisis and recent Eurozone debt crisis) thereby given rise to financial instability and economic uncertainties.

In the full period, there is bidirectional asymmetric effect between UK and US, suggesting that bad news originating from US tend to cause higher volatility in the UK and vice versa. Similarly, negative news increase volatility in a bidirectional way in periods of interwar/WW2, Bretton Woods system and pre-UK exchange controls. In period of post-UK exchange controls, UK market's current volatility increases more in response to the negative news in the US market, but not vice versa. Conversely, in post-EMU period, the US market's current volatility increases more in response to the negative news in the UK market, but not vice versa. The LR test soundly reject the null of absence of asymmetric effects between the two markets.[49] The result for post-EMU period is consistent with findings by Panopoulou and Pantelidis (2009) on volatility transmission between UK and G7 countries. Although, this study was performed prior to 2004 without accounting for asymmetric information and therefore does not provide evidence of the nature of interdependence between the markets in more recent years. Overall, these results suggest that the transmission of shocks and volatility between these markets have essentially been influenced by increasing market integration, financial liberalisation and globalisation.

The results of diagnostic tests indicate that most of the serial correlation in the standardised residuals and squared residuals have been captured in the analysis of volatility dynamics of both UK and US stock return series. To the same extent, the ARCH LM tests indicate absence of

[49] The LR statistics for the null H_0: $\delta_{11} = \delta_{22}$ calculates to 24.61 so that the null of absence of asymmetric effects is rejected at standard significance levels.

ARCH effects in standardised residuals for most periods, which suggests that conditional heteroskedasticity has been largely captured in this series. The sign bias tests show evidence of asymmetric volatility, indicating stronger effect of 'negative news' on volatility. Therefore, the ASY BEKK model adequately captures the asymmetry in the volatility process of the markets.

In summary, we find that the UK and US past shocks are more important in predicting future volatility than past volatility for the entire period. However, the post-EMU result indicates that both UK and US past shocks and volatilities can significantly predict future volatility. This suggests that the establishment of Euro currency has increased financial linkages between these two markets, which may limit diversification benefits and intensify risk of financial contagion. We conclude that due to US global financial dominance, the US past shocks play a pivotal role in explaining the time dynamics of conditional volatility of UK stock market and should hence be taken into consideration when forecasting volatility of future UK stock returns.

Table 2.6: Estimation of Bivariate Asymmetric GARCH BEKK (*1*,*1*)

$$h_{11,t} = c_{11} + \left(\alpha_{11}^2\varepsilon_{11,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1}\right) + \left(\delta_{11}^2\eta_{11,t-1}^2 + 2\delta_{11}\delta_{21}\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}^2\eta_{22,t-1}^2\right)$$

$$h_{22,t} = c_{22} + \left(\alpha_{12}^2\varepsilon_{11,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{22}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1}\right) + \left(\delta_{12}^2\eta_{11,t-1}^2 + 2\delta_{12}\delta_{22}\eta_{11,t-1}\eta_{22,t-1} + \delta_{22}^2\eta_{22,t-1}^2\right)$$

	Full period 1935 - 2015		**Interwar/WW2 1935 - 1945**		**Bretton Woods 1945 - 1971**		**Pre-UK Exc. Cont. 1971 - 1979**		**Post-UK Exc. Cont. 1979 - 1990**		**Pre-EMU 1990 - 1999**		**Post-EMU 1999 - 2015**	
Variables	$h_{11,t}$ (UK)	$h_{22,t}$ (US)	$h_{11,t}$ (UK)	$h_{22,t}$ (US)	$h_{11,t}$ (UK)	$h_{22,t}$ (US)	$h_{11,t}$ (UK)	$h_{22,t}$ (US)	$h_{11,t}$ (UK)	$h_{22,t}$ (US)	$h_{11,t}$ (UK)	$h_{22,t}$ (US)	$h_{11,t}$ (UK)	$h_{22,t}$ (US)
$h_{11,t-1}$	0.921*** (0.004)	4 x 10^{-6} (6 x 10^{-6})	0.837*** (0.018)	0.000 (0.001)	0.882*** (0.014)	2 x 10^{-9} (4 x 10^{-7})	0.902*** (0.015)	2 x 10^{-5} (4 x 10^{-5})	0.895*** (0.019)	5 x 10^{-4} (1 x 10^{-3})	0.909*** (0.021)	2 x 10^{-3} (3 x 10^{-3})	0.947*** (0.013)	3 x 10^{-3} (2 x 10^{-3})
$h_{22,t-1}$	1 x 10^{-6} (3 x 10^{-6})	0.935*** (0.006)	6 x 10^{-6} (2 x 10^{-5})	0.958*** (0.007)	3 x 10^{-5} (4 x 10^{-5})	0.922*** (0.009)	8 x 10^{-4} (2 x 10^{-3})	0.949*** (0.009)	5 x 10^{-6} (4 x 10^{-5})	0.942*** (0.012)	2 x 10^{-4} (1 x 10^{-3})	0.925*** (0.017)	3 x 10^{-3} (3 x 10^{-3})	0.874*** (0.013)
$h_{12,t-1}$	-0.002 (0.003)	0.004 (0.003)	-0.005 (0.008)	-0.039 (0.024)	-0.009 (0.007)	-0.009 (0.009)	-0.017 (0.026)	0.009 (0.008)	-0.001 (0.018)	0.013 (0.022)	0.008 (0.023)	-0.029* (0.017)	-0.034** (0.017)	0.030*** (0.012)
$\varepsilon_{11,t-1}^2$	0.055*** (0.005)	0.001*** (0.001)	0.113*** (0.029)	0.001 (0.003)	0.069*** (0.013)	0.000 (0.001)	0.067*** (0.014)	0.000 (0.000)	0.047*** (0.018)	0.000 (0.000)	0.059*** (0.014)	0.015** (0.006)	0.009* (0.005)	0.021*** (0.006)
$\varepsilon_{22,t-1}^2$	0.001** (0.001)	0.018*** (0.002)	0.006** (0.003)	0.001 (0.003)	0.001 (0.001)	0.006* (0.004)	0.006 (0.006)	0.012** (0.006)	0.005 (0.006)	0.024*** (0.006)	0.000 (0.001)	0.007 (0.008)	0.012** (0.005)	0.053*** (0.009)
$\varepsilon_{11,t-1}\varepsilon_{22,t-1}$	0.017*** (0.003)	-0.007*** (0.002)	-0.051*** (0.010)	0.003 (0.003)	0.019** (0.009)	0.001 (0.002)	-0.041** (0.018)	-0.004 (0.003)	0.031** (0.015)	-0.001 (0.011)	0.007 (0.011)	-0.021 (0.014)	0.021*** (0.006)	-.067*** (0.013)
$\eta_{11,t-1}^2$	0.047*** (0.006)	0.003*** (0.001)	0.098*** (0.028)	0.021* (0.012)	0.056*** (0.016)	0.002 (0.002)	0.039* (0.022)	0.002 (0.002)	0.051 (0.037)	0.019** (0.008)	0.000 (0.002)	0.001 (0.002)	0.092*** (0.017)	0.021*** (0.007)
$\eta_{22,t-1}^2$	0.001 (0.001)	0.060*** (0.005)	0.002 (0.001)	0.058*** (0.012)	0.002 (0.001)	0.101*** (0.012)	0.021 (0.016)	0.064*** (0.015)	0.027*** (0.018)	0.008 (0.008)	0.007 (0.007)	0.083*** (0.022)	0.001 (0.003)	0.073*** (0.019)
$\eta_{11,t-1}\eta_{22,t-1}$	-0.012*** (0.004)	0.028*** (0.003)	0.025** (0.010)	0.069*** (0.019)	0.019** (0.008)	0.031*** (0.011)	-0.057* (0.031)	-0.022** (0.011)	-0.074** (0.037)	-0.025 (0.015)	0.002 (0.016)	0.015 (0.025)	-0.019 (0.029)	0.078*** (0.010)
Q(12)	101.8***	19.38***	8.906	16.02	25.32***	5.532	14.20**	2.864	27.32***	14.80**	18.88***	8.054	121.4***	167.4***
$Q^2(12)$	59.32***	1.272	12.20*	17.98	110.4***	3.019	4.599	1.362	1.985	7.884	7.102	3.186	7.824	9.916
ARCH	8.720*	5.844	0.942	10.08**	19.15***	3.019	4.599	1.362	1.985	7.467	3.156	2.755	6.012	8.326*
Sign	0.060* (0.036)	0.148*** (0.035)	0.146 (0.143)	0.266*** (0.081)	-0.124 (0.082)	0.115* (0.066)	0.057 (0.067)	-0.041 (0.066)	0.056 (0.061)	0.262 (0.222)	-0.156** (0.072)	0.105 (0.096)	0.062 (0.056)	0.023 (0.051)
Summary of significant spillover effects														
	Full period		**Interwar/WW2**		**Bretton Woods**		**Pre-UK Exc. Cont.**		**Post-UK Exc. Cont.**		**Pre-EMU**		**Post-EMU**	
Volatility spillover											Unidirectional		Bidirectional	
Shock spillover	Bidirectional		Unidirectional		Unidirectional		Unidirectional		Unidirectional				Bidirectional	

Notes: The superscripts '*', '**'and '***' denote significant levels at 10%, 5% and 1%. Standard errors are in parenthesis. The Ljung-Box test the autocorrelation in the standardised residuals (Q) and squared residuals (Q^2) up to 12 lags. The ARCH LM test for heteroscedasticity in standardised residuals up to lag 4. Engle and Ng (1993) Sign Bias test for significance of $I(\varepsilon_t^i < 0)$ for *i = 1 and 2*. The summary of the shock and volatility spillovers indicate blank if there are no cross-markets effects; unidirectional if there are unilateral transmission effects and bidirectional if there are feedback transmission effects.

2.5.5 Volatility Impulse Response Functions

This section examines the influential role that shocks play in the dynamic adjustment of volatility in both markets and the persistent nature of these transmission effects. Figure 2.12 demonstrates the volatility impulse response functions (VIRFs) over a 10-day horizon for conditional variance and 300-day horizon for covariance. The four observed historical shocks considered in this empirical exercise include the 19th October 1987 stock market crash, the 11th September 2001 terrorist attacks, the 19th March 2003 Iraq invasion, and the 15th September 2008 stock market crash. We use specific dates in order to evaluate the direct effect of the shocks of the first notice of crisis on stock return volatility. These historical episodes have profound implications for risk management and financial market stability.

For the first episode, the volatility impulse response to the shock on 19th October 1987 (Black Monday) indicates a positive impact on the expected conditional variance illustrated by a 35% increase in the UK market and a 2.8% increase in the US market. Before the effect of the shock decreases too zero, the UK market absorbed the shock in 9 days, while the US market absorbed the shock in 2 days. Similarly, the impact is positive for the covariance as illustrated by a 4% increase and steadily decline over a period of 150 days after the initial shock. The magnitude and speed of adjustment can be attributed to the unanticipated nature of the stock market crash, which recorded the largest one-day loss ever in US, UK and other developed countries. Some reasons put forward by analysts for this monumental loss include the effect of trading programs, market illiquidity, psychological panic and stock overvaluation (see for example, Bozzo, 2007; Bookstaber, 2007; Annelena, 2007).

For the second episode, the response to the shock on 11th September 2001 (terrorist attack) in the UK market indicates that a positive impact has been exerted onto the expected conditional variance which can be quantified in a 12% increase. In contrast, the impact is negative for the US market, which suggests that expected conditional variance following the shock tend to decrease. However, the speed of adjustment in the US is instantaneous while it took as many as 8 days for the UK market to absorb the shock, and then decreases to zero. The reason for this adjustment in US can be attributed to the temporary shutdown of NYSE and NASDAQ until 17th September 2001 because of an anticipated market chaos, panic selling and cataclysmic loss of value in the wake of the attacks. Perhaps, the immediate response by the government in shutting down the US stock exchange prevented the shock in resulting into stock market meltdown. In addition, the impacts are negative and insignificant for the covariance between the UK and US markets although it tends to gradually disappear within a longer period (about

200 days after the initial shock). This suggests that shocks to financial market originating from terrorist attacks can be curtailed by the government's prompt stringent response, for example temporary shutdown of stock exchange, in order to prevent market panics, chaos and crash.

For the third episode, the response to the shock on 19th March 2003 (Iraq invasion) in both markets indicate a negative impact on volatility suggesting that expected conditional variance following the shock tend to decrease (0.001% decrease in the US and 0.030% decrease in the UK). The US market instantaneously adjusted to the shock while adjustment in the UK market took about 8 days. These adjustments can be attributed to the fact that the market had long before anticipated the Iraq invasion and did not come as a surprise. Similarly, the impacts are negative and insignificant for the covariance between the two markets. The speed of adjustment for the covariance took as much as 175 days. This further suggests that political shocks lead to a decrease in volatility perhaps due to the rational expectation of agents that have incorporated the news in market prices before the episode occurred.

For the fourth episode, the response to the shock on 15th September 2008 (collapse of Lehman Brothers) indicates a positive impact on the conditional variance illustrated by a 13% increase in the UK and 0.6% increase in the US market. It took 8 days for the UK market to absorb the shock and 3 days for the US market to absorb the shock. The impact is positive for the covariance as illustrated by a 0.45% increase and gradually decline over a period of 275 days after the initial shock. Apparently, the high magnitude and speed of adjustment explains the severity of the global financial crisis leading to the worst global recession in recent times. The collapse of the 4th largest investment bank in the US significantly increased volatility in the UK and US, thus, suggesting some form of market contagion.

In summary, the impact of political shocks on volatility tend to be negative and insignificant while economic shocks tend to be positive and highly significant in the UK and US markets. However, the UK market is more affected by economic and financial shocks than the US market. This corroborates with the bidirectional shock spillover, such that the spill over of shocks from US increases volatility more in the UK than the other way round. A plausible reason for the significant reaction to external shock in UK market may be due to higher exposure to market risk faced by investors. This findings corroborate with existing evidence on the rate of decay of volatility shocks (see Leachman and Francis, 1996; Panapoulou and Pantelidis, 2009). The origin of these political and financial crisis episodes stemmed from the US and we conclude US being a 'global centre' plays a significant role in the transmission of shocks to UK (see Li, 2007; Kenourgios *et al.*, 2011). We argue that though the US transmit shocks to other markets, the US has been able to develop robust policy and regulatory framework that will mitigate internal and external shocks, hence quickly recovering from shocks and rapidly stabilising its financial markets.

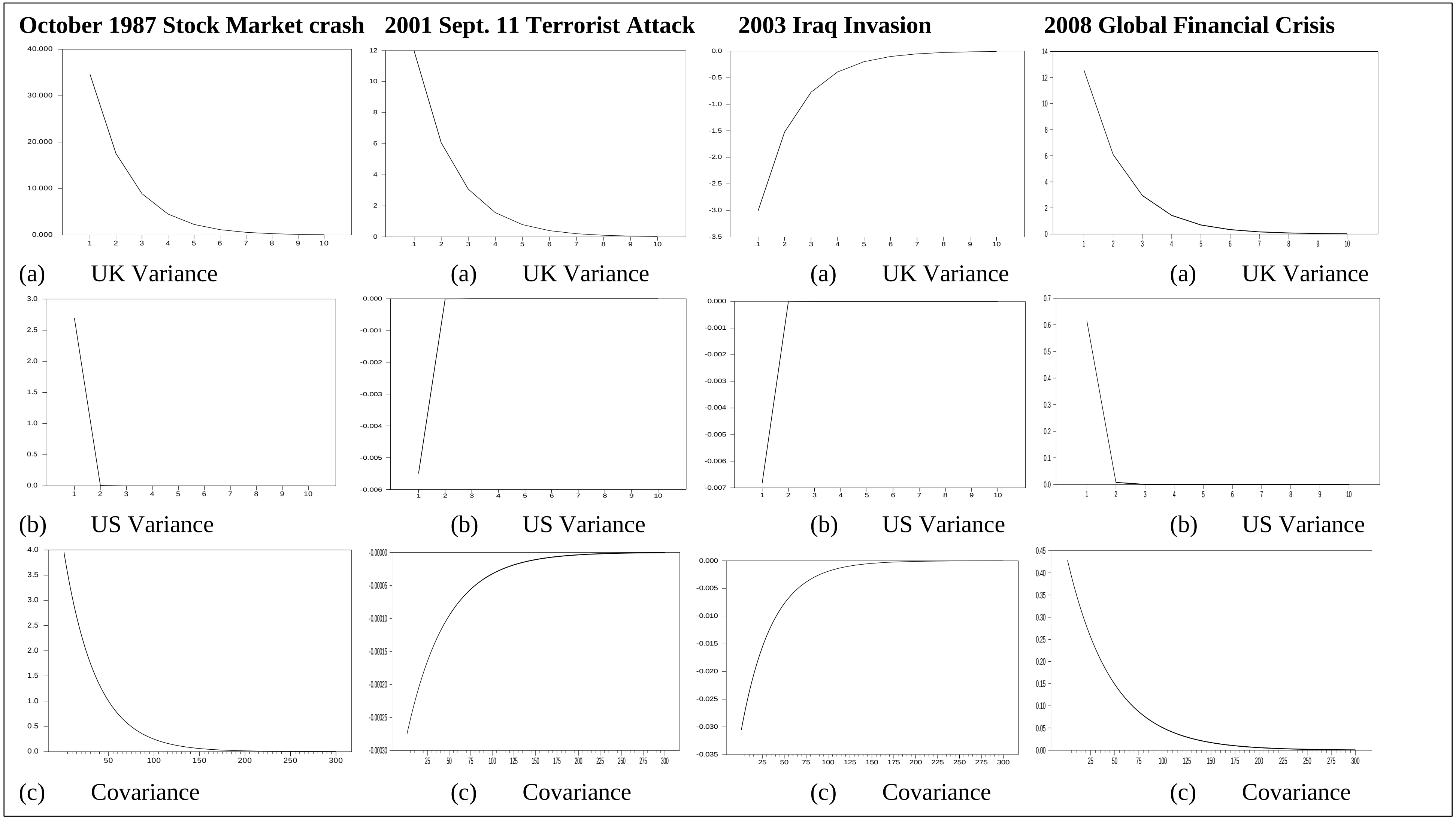


Figure 2.12: The VIRFs for Macro-Financial and Political Episodes

2.5.5 Time-Varying Conditional Correlations

There is a general belief among scholars that there has been a secular trend toward global interdependence since World War II. Figure 2.13 demonstrates that the estimated conditional correlations computed from the ASY BEKK model exhibited substantial variations throughout the periods. The stock market correlations between UK and US from 1935 to 2015 have varied widely over time with an estimated 50 and 95 percentiles of 0.223 and 0.536 respectively. The period of Interwar/WW2 witnessed a high significant variation from negative to positive values with an estimated 50 and 95 percentiles of 0.111 and 0.488 respectively. The negative stock correlations particularly between 1941 and 1945 can be attributed to global political instability, isolationist economic policies and financial market instability.

Furthermore, wide positive variations in stock correlations prevailed during the period of Bretton Woods system (1945 – 1971) though the estimated 50 percentile of stock correlations declined by 14% to 0.095. The underlying reasons for decrease in stock market integration can be ascribed to exchange rate constraints, excessive capital controls and divergent macroeconomic policies. We further attribute the low correlation to the escalation of the Vietnam War and the simultaneous establishment of the Great Society Program which led to accelerated global rate of inflation and rising balance of payment deficit.

Consequently, the collapse of the fixed exchange rate regime in 1971 triggered less variation between negative and positive values with the 50 and 95 percentiles of stock correlation increasing slightly by 10% on average to 0.105 and 0.316, respectively. In the aftermath of the Nixon Shock, many developed countries adopted the floating exchange rate regime which increased unpredictability of exchange rates and economic volatility. However, there has been informal cooperation by Central Banks of leading developed economies (US, UK, Japan and Germany) to safeguard the integrity of the international monetary system, prevent financial instability and stabilize exchange rates by intervening in the currency markets since the end of the rule-based monetary system. Due to the abolition of UK exchange controls in 1979 and further deepening of financial liberalisation in the two markets, time-varying correlation increased dramatically by 152% to 0.265 on average. This suggests that increase capital account liberalisation and financial depth contributes to higher stock market integration.

In pre-EMU period, stock correlation further increased by an average of 25.57% to 0.333 which can be attributed to the gradual take-off of the proposed EMU. Since the full take-off of EMU in 1999, correlation has increased significantly to an average of 0.574. In fact, correlation significantly increased during the great recession and slow recovery period between 2008 and

2012 but has gradually declined to the pre-crisis period (2002 – 2006). The gradual increase in stock market correlations since the elimination of all forms of exchange controls and gradual phasing-in of EMU clearly portends that the markets are integrating, hence potentially reduce the gains from portfolio diversification and aggravate risk of market contagion. These results corroborate with the findings of increasing stock correlations by previous scholars such as Kim *et al*., (2005); Cappiello *et al*., (2006); Aslanidis *et al.*, (2010). Although, these previous studies considered other GARCH variants and used limited dataset for their analysis.

We run a test statistic for equality of correlation coefficients across the 6 subsamples. The results in Table 2.7 show that we reject the null hypothesis of equality of correlation in each case. This suggests that there have been significant increases in the time-varying correlations of the stock market returns from one period to another except from period 1 to period 2. This further justifies that subsample analysis provides more insight into the dynamic nature of the stock market integration process between the UK and US.

The spikes in stock correlations coincided with the intense period of crisis such as the 1971 international monetary system crisis, October 1987 stock market crash, 1998 Asian financial crisis, the internet bubble bust and the 2008 stock market crash. A number of empirical studies have described significant increase in correlations caused by shocks as market contagion. Following Chiang *et al.* (2007), we conjecture that during period of high volatility, correlation coefficients between UK and US markets are likely to increase significantly.

We report in Table 2.7 evidence of market contagion by testing if there are significant jumps in correlation levels from stable to crisis periods. The equality of correlation levels between the crisis and stable periods, indicate that we reject the null hypothesis that the correlation are the same for these markets. For external crisis (1973/1974 oil shock and 1997/1998 Asian/Russia crisis), the average conditional correlations between UK and US increase during negative shocks than stable periods, whereas the 1994/1995 Mexican currency crisis, the average conditional correlations decline. The evidence of no contagion between UK and US markets during the Mexican crisis is closely associated with the findings of Bekaert *et al.* (2005). For crisis originating from the US (e.g. 1987 stock market crash, dot-com bubble bust and 2007/2009 global financial crisis), the conditional correlations are higher during the crisis periods than stable periods. On the contrary, crisis originating from UK (e.g. 1992/1993 European Monetary system crisis) reduces conditional correlation in the crisis period compare to stable period. This suggests that stock market integration are much higher during extreme headwinds (i.e. crisis originating from the US or regional powers) than tailwinds. These findings corroborate with the evidence of contagion from the US to a plethora of European stock markets during times of high world market volatility (see Baele, 2005).

The excessive increases in stock volatility and cross-market correlation during crisis periods compared to stable periods support existing evidence on 'contagion' (see Arshanapalli *et al.* 1995; Liu *et al.*, 1998; Edward, 2000; Sheng and Tu, 2000; Forbes and Rigobon, 2002; Hon *et al.* 2004; Chiang *et al.*, 2007; Kenourgios *et al.*, 2011 Baur, 2012; Dimitriou *et al.*, 2013).[50] The difference in the magnitude between the crisis and stable periods is significantly higher during the October 1987 stock market crash (0.263) and 2007-2009 global financial crisis (0.166). This further suggests the leading role of the US market as a "global financial centre" influencing UK and other economies.

For emphasis, most of these negative shocks originate from the US market and induce simultaneous price movements in the UK markets, providing evidence for market contagion. The increased stock correlations can also be explained such that the information asymmetries decrease during crises, because investors are more focused on easily available public information (see Bekaert *et al.*, 2014). This suggests that international diversification opportunities are limited during crises period when they are probably most required. However, the systematic fall in excessive correlation perhaps due to financial globalisation reversal may open a new channel of diversification benefits to international investors (see Baele, 2005). Overall, the significant increase in correlation following a shock, implies that crisis accelerates the integration process between the UK and US financial markets.

We show the kernel density estimate and normal density of the UK and US stock correlations in Figure 2.14. The graphs reveal that the kernel density estimates follow approximately the same pattern as the normal densities predicted although with asymmetries and fat tails. The normal density typically shows the normal bell-shaped while the kernel density estimates have a less normal bell-shaped. Apart from the full period, interwar/WW2 and post-EMU periods, excess kurtosis is present in all most sub-periods. Similarly, stock correlation density estimates show a much more positively skewed density in all periods except for the negative skewness exhibited in post-EMU period. Overall, the stock correlation density estimates exhibit large pointed peaks and a long tail extending to the left in most periods.

Furthermore, Figure 2.15 shows the quantile normal (Q-norm) distribution plots of the percentiles of the empirical distribution of UK and US stock correlations against the theoretical distribution (i.e. inverse normal). If the data is assumed to be normally distributed, we will

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[50] Market interdependence is defined as a continued cross-market correlations at high levels.

expect to observe a linear plot (45^o line) for some random movements in the data. We would expect to see the upper tails of the Q-norm plot bending upwards and the lower tail turning downwards for a heavy-tailed distribution. On the other hand, an *S*-shaped is expected with the lower tails turning upwards and upper tail bending downwards for a short-tailed distributions. Taking a cursory look at the Q-norm plots, we observe that they are linear in the middle with varying degrees during the periods. However, there seems to be systematic deviations from the 45^o line at the lower and upper tail. For instance, the interwar/WW2 period vividly shows a very strong departure from the line at the negative end of the plot, suggesting clearly it is not behaving like normal distribution up in the lower tails. Likewise, pre-EMU period also show a very strong departure from the line at the positive end of the plot, suggesting plainly it is not behaving like normal distribution up in the upper tails. The first instance shows a strong indication of a heavy left tail while the second reveals a heavy right tail. The Q-norm plot of the Bretton Woods System period indicates the most symmetrical about zero and least deviation from the 45^o line of all the sub-periods.

In summary, the low correlation in the first four decades can be ascribed to the rule-based monetary system, macroeconomic divergence, economic regionalism and protectionism, whereas the rising correlation since the 1970s can be associated with the principle-based monetary system, global capitalism, economic integration, financial liberalisation and the introduction of the euro currency. Particularly, the gradual phasing-out of capital controls and deepening financial liberalisation since 1979 have increased cross-listing of shares, growth in foreign ownership of listed firms and cross-border capital flows.

Table 2.7: Average Conditional Correlations

Episodes	**Crisis period**	**Stable period**	**Equality of mean**
Oil shock (1973 – 1974)	0.249*** (28.52)	0.097*** (8.006)	0.151*** (11.53)
October 1987 market crash	0.434*** (11.99)	0.129*** (7.952)	0.305*** (6.418)
European monetary system crisis (1992 – 1993)	0.253*** (42.78)	0.297*** (35.73)	-0.043*** (-4.719)
Mexican currency crisis (1994 – 1995)	0.252*** (46.06)	0.287*** (43.29)	-0.035*** (-3.991)
Asian and Russian crisis (1997 – 1998)	0.388*** (75.17)	0.241*** (40.58)	0.147*** (15.46)
Dot-com bubble bust (2000 – 2002)	0.382*** (76.71)	0.373*** (83.25)	0.009 (1.359)
Global financial crisis (2007 – 2009)	0.503*** (120.0)	0.339*** (74.19)	0.164*** (29.92)
Equality of Correlation			
	Test (1)	**Test (2)**	**Equality of Mean**
Period 1 = Period 2	0.133	0.099	0.039*** (10.00)
Period 2 = Period 3	0.098	0.112	-0.012*** (-5.523)
Period 3 = Period 4	0.112	0.244	-0.132*** (50.62)
Period 4 = Period 5	0.249	0.337	-0.088*** (34.59)
Period 5 = Period 6	0.337	0.535	-0.198*** (67.78)

Notes: The superscripts '*', '**'and '***' denote significant levels at 10%, 5% and 1%. The equality of conditional average correlation between crisis and stable periods is tested using the two-sample t-tests. The *t*-statistics are shown in parenthesis.

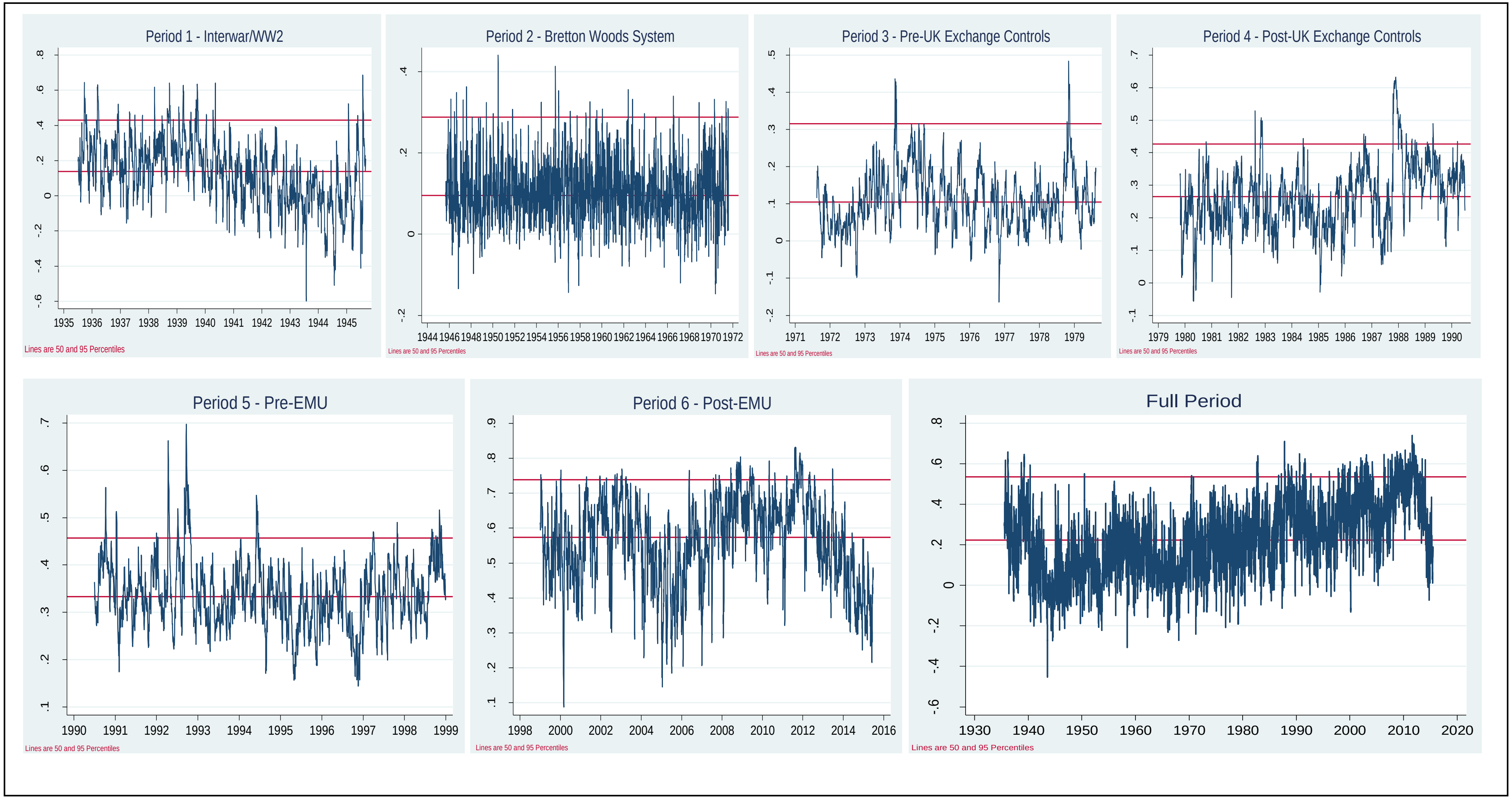


Figure 2.13: Stock Conditional Correlation between UK and US Markets

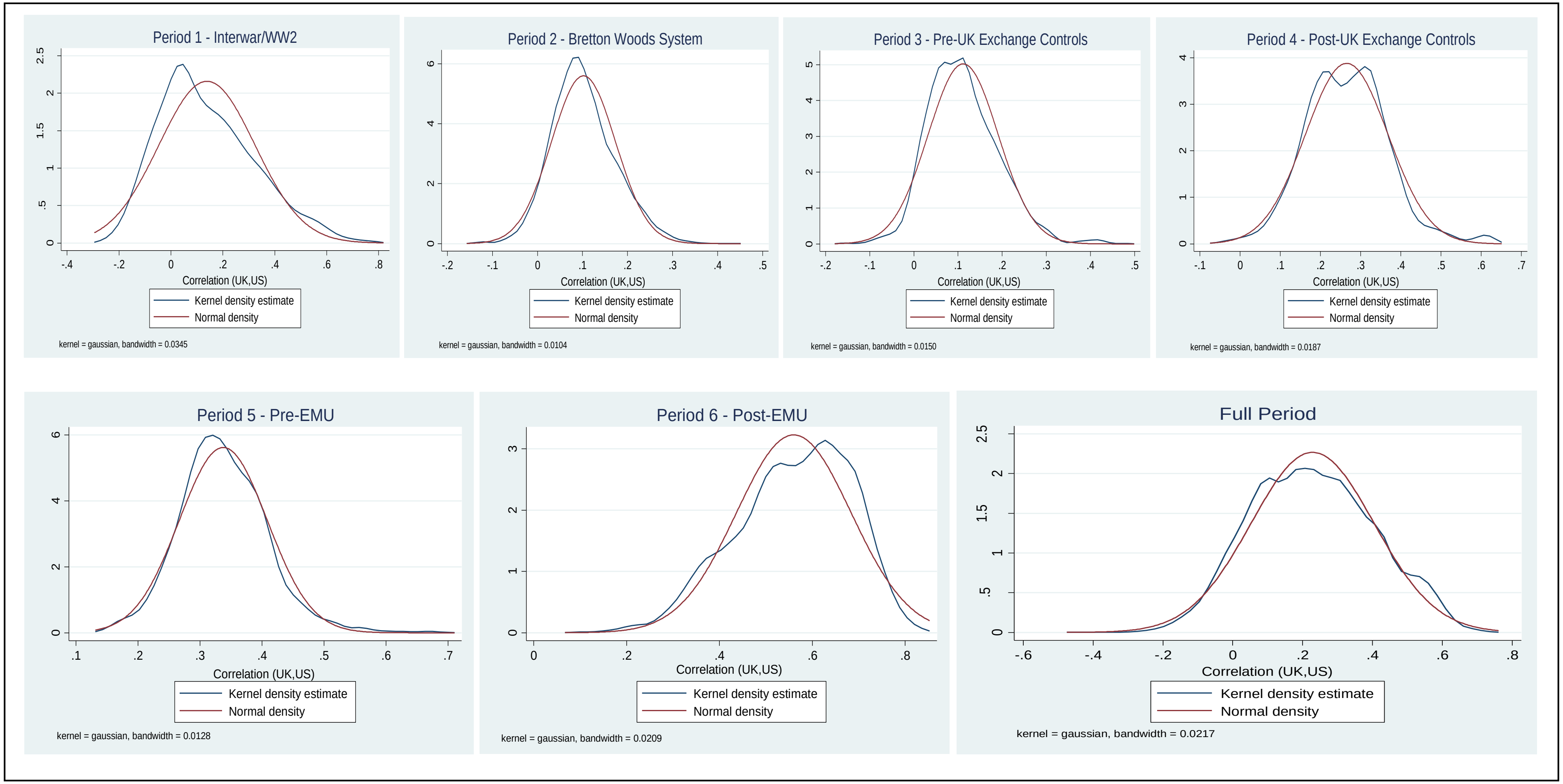


Figure 2.14: Kernel Density Estimates of UK and US Stock Correlations

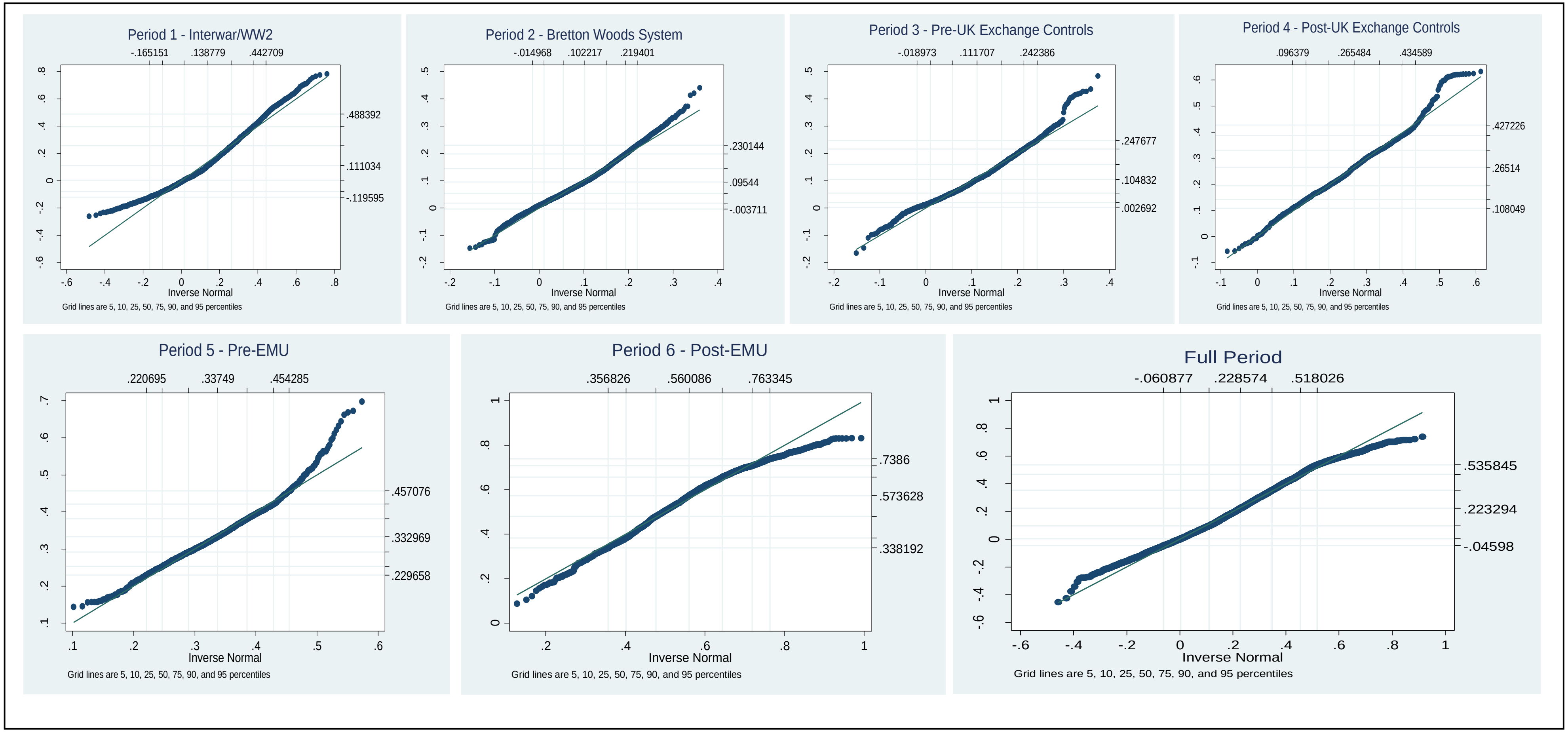


Figure 2.15: Quantiles of Normal Distribution of UK and US Stock Correlations

2.5.6 The Determinants of Stock Market Integration

We use the bivariate DCC-GARCH model to estimate the monthly conditional correlations between UK and US macroeconomic fundamentals (industrial output, consumer price inflation, interest rate spreads) and univariate GARCH model to estimate the monthly volatility of foreign exchange rates, gold and oil prices. Arguably, these factors are considered to drive the stock integration process between UK and US over time.

Table 2.8 shows the pairwise correlation between the monthly stock markets co-movement (US and UK) and the aforementioned macroeconomic correlation and financial indicators volatility. The unconditional correlations among the variables are mostly positively low and significant, which suggests that multicollinearity between variables is not a problem. In addition, we provide the plots of their conditional correlations and volatilities in Figure 2.16. They demonstrate variations between negative and positive values of the output and yield spread correlations. Since 1985, the correlations between UK and US yield spreads have increased significantly, which can be attributed to growing flow of portfolio investments, market depth and liquidity. Between 1935 and 1971, low volatility of gold and oil prices persists because of the Bretton Woods agreement of fixed exchange rate regime. From 1971 onward, the commodity prices volatility became persistently high as a result of increased financial liberalisation. The significant spikes in oil price volatility was caused by the 1973 oil crisis, the 1990/1991 Persian Gulf War and 2008 oil price crash. The real exchange rate volatility is very low and stable between 1935 and mid-1950s and has risen significantly afterwards.

Table 2.8: Pairwise Correlation between Stock Correlation and Explanatory Variables

	Stock corr.	Output corr.	Inflation corr.	Interest rate corr.	Oil vol.	For. Exc. vol.	Gold vol.	Stock mkt vol.
Stock corr.	1.000							
Output corr.	0.065**	1.000						
Inflation corr.	-0.078***	-0.011	1.000					
Int. rate corr.	0.536***	0.009	-0.032***	1.000				
Oil vol.	0.516***	0.119***	0.154***	0.499***	1.000			
For. Exc. Vol.	0.169***	0.054*	0.182***	0.142***	0.302***	1.000		
Gold vol.	0.396***	0.088***	0.440***	0.289***	0.598***	0.379***	1.000	
Stock mkt vol.	0.125***	-0.039	0.293**	0.091***	0.167***	0.180***	0.424***	1.000

Notes: '*', '**' and '***' denote 10%, 5% and 1% significant levels.

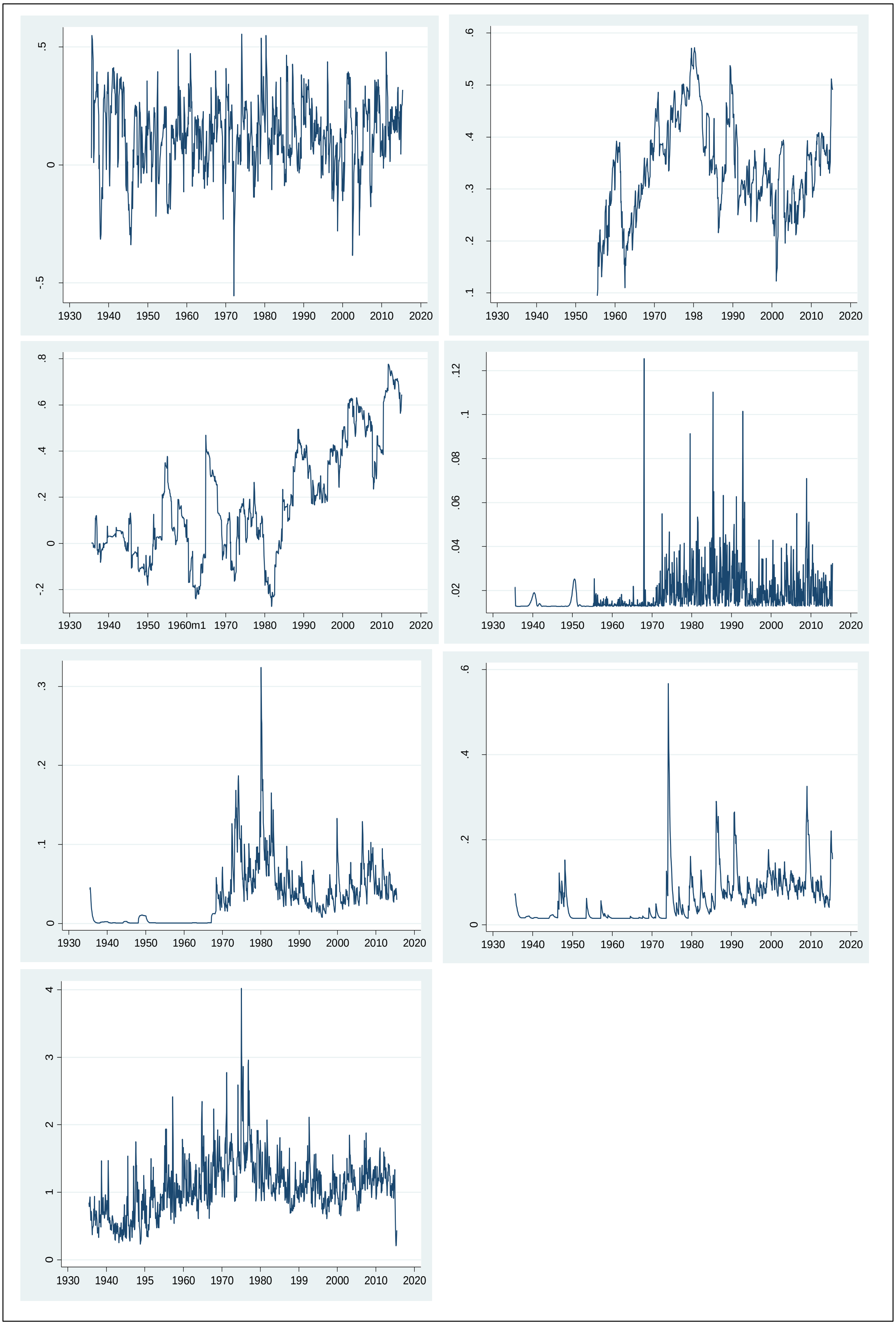


Figure 2.16: Macroeconomic Correlations and Financial Volatilities

Table 2.9 reports the empirical estimates for the mixed date sampling (MIDAS) regression model. This model achieves higher power test of the determinants of cross-border stock market linkages and eliminates the biased estimates attributed to information loss based on an equal weighting scheme. In the full sample period, the goodness of fit (R^2) suggests that 45.4% of the variation in the stock correlation coefficients is explained by the variation in the explanatory variables, which is evidence of a reasonably good fit. The lowest goodness of fit occurred in period 2 with an R^2 of 7.7% while the highest goodness of fit occurred in period 6 with an R^2 of 48.4%. It is important to note that the relationship between the stock market integration and these exogenous factors have important implications when designing investment portfolios, regulating the financial system and engaging in robust policy-making.

In the full period, convergence in macroeconomic fundamentals (i.e. output growth, yield spread and inflation) increases stock market integration with estimated values of 0.146, 0.223 and 0.336, respectively. Arguably, the divergence of output growth, interest and inflation rates have declined through convergence in the real economy and as well in monetary policies, hence market integration has been stimulated by macroeconomic stabilisation policy. This suggests that the convergence of business cycle, monetary policy stance and inflationary environment has stimulated stock market integration over the last 80 years. This supports the findings of positive relationship between stock market integration and macroeconomic convergence by Phengpis *et al.* (2004), Kim *et al.* (2005), Syllignakis and Kouretas (2011). In contrast to expectation, increases in volatility of gold and oil prices have propelled stock market integration with estimated coefficients of 0.682 and 0.505, respectively. There have been large swings in gold and oil prices, particularly during crises, wars and adverse weather conditions. These periods of high uncertainties will increase the volatility of the international financial markets, hence leading to rise in stock market correlations. Possibly, if commodity is a hedge against high stock market volatility, then higher demand could increase volatility of commodity prices, hence positively related with stock market integration. Incidentally, the relationship between market integration and exchange rate volatility is insignificant. This corroborates with Kim *et al.'s* (2005) evidence that stock market integration is not very sensitive to exchange rate volatility (see also Bodart and Reding, 1999). The reason may be due to the stronger effect of extremely low volatility prevalent during the period of Bretton Woods system of fixed exchange rate regime, which eventually got terminated in 1971.

On the basis of stock market characteristics, stock market volatility is not an important driver of stock market integration, as the coefficient is not significant. This suggests that the risk-return trade-off does not converge between both markets. The insignificant relationship between stock market volatility and correlation corroborates with Pretorious (2002). However, the change in the UK index constituents reduces integration significantly, whereas the change in the US index constituents increases integration significantly. This may suggests that in contrast to UK stock index composition, the reconstruction of the US stock index to reflect growth stocks, industry size and market capitalisation will lead to increase in integration between US and UK. The size of the US stock market and her economic dominance invariably drive the integration process.

The following political and economic episodes that increase stock market integration than usual include, World War II, Korean War, Oil shock, 1987 stock market crash, Iraq-Kuwait war, EMS crisis, Asian and Russian crisis, dot-com bust, whereas the Vietnam war, Afghanistan war, and Eurozone debt crisis reduce integration. It is important to note that the effect of wars are different which may be due to the connection between high-intensity conflicts vis-à-vis changes in economic performance. The increase in stock market correlations in times of currency crisis (e.g. European currency crisis, Mexican crisis and Asian currency crisis) corroborates with Baele's (2005) findings. The surge in integration during crisis periods suggests some forms of contagion that cannot be explained by economic fundamentals. The influence of non-economic fundamentals on stock market integration reinforces evidence of market contagion (see Baig and Goldfajn, 1999; Hon *et al.* 2007; Kenourgious *et al.* 2009).

In the interwar/WW2 period, business cycle convergence stimulates stock market integration such that a one unit increase in output growth convergence boosts integration by 98 basis points. In a similar fashion, inflation convergence between UK and US economies leads to an increase in stock market integration by 202 basis points. A one unit increase in interest rate convergence strengthens integration by 194 basis points. On the contrary, interest rate divergence causes a decrease in integration by 248 basis points. This may be due to the instability in the political and economic given rise to divergent market reactions of investors in the bond market. This corroborates with the findings of Piplack and Straetmans (2009) who document evidence of negative relationship between bond and stock markets during times of market turmoil. As expected, we find that the lower the oil price volatility the higher the stock market integration. In addition, the evidence further shows that the 1937/1938 and 1944/1945 economic recessions in the UK and US increase the level of integration. The evidence that equity market correlations are higher during recession is consistent with Ragunathan *et al.,* (1999), Buttner and Hayo (2011). Similarly, the WW2 episode significantly improves stock market integration by 71 basis points. This indicates that the period of crisis significantly increases integration than non-crisis period, suggesting some form of contagion. Looking at stock market integration from the perspective of stock market characteristics, we find that the higher the stock market volatility, the higher the integration between UK and US. This demonstrates that financial market instability prevalent during the WW2 raises volatility sharply, hence increased integration. Finally, the change in the components of the FT30 and Dow30 significantly reduces integration between them, which may have been caused by industry dissimilarity.

In the period of Bretton Woods system, we find that macroeconomic divergence (business cycles and monetary policy) between UK and US significantly decreases stock market integration. This further justifies the weakened stock market integration prevalent in this period. The fixed exchange rate regime adopted by these countries although reduced macroeconomic and financial volatilities on the one hand, it also aggravated divergent fiscal and monetary policies, on the other hand. Additionally, the changes in the components of the UK and US stock market indices significantly improve stock market integration. The 5 double-dip recessions (1951/1952, 1955/1958, 1966/1966 and 1968/1971) experienced in the UK strengthen integration by 7 basis points. For the episodes, the 1950/1953 Korean War increases integration by 18 basis points while the 1959/1974 Vietnam War decreases integration by 27 basis points.

In the period of pre-UK exchange controls, inflation divergence significantly reduces the integration process between UK and US stock markets. We argue that the period of rising inflation triggers high level of uncertainty that makes decision making of market participants difficult thereby limiting and distorting cross-border investment transactions, hence a decline in stock market integration. This further suggests that the floating exchange rate regime generates unpredictability of exchange rates, increases economic volatility and widens bond yield spreads. In contrast to expectation, the high commodity volatility (gold and oil) stimulates the integration process. Similarly, stock market volatility positively influences stock market integration. The changes in the UK and US stock index constituents increase integration significantly, suggesting perhaps similarity in industrial composition of the two economies has stimulated integration. The 1973/1975 recession in the US significantly diminishes integration by 13 basis points. The 1973/1974 oil shock episode significantly increases integration by 19 basis points, indicating that crisis periods drive stock market integration.

In the period of post-UK exchange controls, macroeconomic fundamentals play no role in the integration process of both markets. However, increases in volatility of foreign exchange rate and gold price stimulate integration. This suggests that deep financial liberalisation and flexible exchange rate regime have led to a surge in international capital mobility through the interest rate and exchange rate channels, hence strengthening the integration process. The stock market turmoil prevalent in this period gave rise to investors' demand for gold as a safe haven, thus propelling the rise in volatility and correlation. This is described as 'flight to quality' phenomenon, such that a sign of crisis in the stock market for instance, triggers increased investors demand for safe assets (e.g. gold and bond), hence raising asset price volatility. This suggests that in periods of severe market shocks, a positive relationship between stock market integration and gold price volatility is plausible because of simultaneous rise in volatility in the stock and commodity markets. This is consistent with the findings that gold or bond markets play an important role as a safe-haven in extreme market conditions (Baur and Lucey, 2010; Baur and McDermott, 2010; Chan *et al.*, 2011). Even though gold market is considered as a safe-haven asset, the increase in gold price volatility is perceived by investors as a signal of increasing risk or uncertainty of macroeconomic and financial conditions. This will increase the cost of hedging against cross-market risk. Finally, the UK recession of 1980/1981 significantly reduces integration by 23 basis points. The 1987 stock market crash significantly increases integration by 48 basis points, suggesting some forms of contagion effects from US where the crisis originated to UK market.

During the pre-EMU period, interest rate convergence has positive impact on stock market integration by 113 basis points whereas, divergence in inflation between the two countries reduces integration by 225 basis points. The inflationary economic policies pursued in the US in the 1990s diverged from the UK's non-inflationary monetary policy as laid down in the Maastricht Treaty, hence the decline in integration. The increases in the volatility of gold and oil prices are important catalyst for more integration. The 1992/1993 European monetary system crisis and Mexican currency crisis decrease stock market integration whereas, the Asian and Russian Crisis and internet bubble episodes significantly increase integration. This suggests that market bubbles and crashes are important drivers of integration, perhaps due to reduced information asymmetries among international investors with a tendency towards converging economic decisions on available public information.

In the post-EMU period, business cycle and interest rate convergence increase stock market integration. However, the divergent inflation rates of the two countries reduce integration by 3 basis points. In contrast to expectation, the peaks in foreign exchange rate and oil price volatilities significantly increase integration. The positive relationship between oil volatility and stock market integration in this period may be due to the invasion of Iraq in 2003 by US and allied forces and the Arab Spring that began in 2011. Also, we argue that though exchange rate volatility has increased, financial market operators have also learned to minimise their hedging costs to mitigate high currency risk, hence there is less degree of market segmentation and high degree of market integration. This contrasts with the previous findings that lower exchange rate volatility stimulates stock market integration (see Fratzscher, 2002; Syllginiakis and Kouretas, 2011; Buttner and Hayo, 2011). We further attribute the increased integration to the impact of financial liberalisation and globalisation via the interest rate and foreign exchange transmission channels. The prolonged double dip recession in UK increases stock market integration by 55 basis points whereas the US recession diminishes integration by 29 basis points. A unit reduction in stock market volatility strengthens integration by 6 basis points. This period further indicates that changes in stock index constituents have no influence on stock market integration, suggesting that integration is no longer sensitive to changes in industrial structure composition. The housing bubble, global financial crisis and Eurozone debt crisis have a positive relationship with stock market integrating, hence suggesting a form of contagion.

In summary, the MIDAS regression model explains 45% of the variation of stock correlation coefficients, suggesting perhaps that about 55% of this variation can be attributed to other economic and non-economic fundamentals not captured in this analysis. The overall results obtained from the MIDAS regression is far better than the standard OLS used by previous empirical literature. In support of existing evidence, macroeconomic fundamentals and financial factors have influenced the evolution of stock market integration over time (see Phengpis *et al.* 2004; Kim *et al.* 2005; and Ehrmann, 2011). Moreover, a number of political, economic and financial historical episodes have influenced stock market integration from one period to another, corroborating with the findings that stock market correlation tend to increase more during turbulent times than in tranquil times (see Cappiello *et al*., 2006; Aslanidis *et al*., 2010; Berger and Ponzi, 2013). Most interestingly, the divergent macroeconomic policies and capital controls between these two economies are arguably responsible for the weak stock market integration in the periods of BWS and pre-UK exchange controls, whereas macroeconomic convergence and financial liberalisation have strengthened stock market integration in other periods.

Table 2.9: MIDAS Regression Estimates

Explanatory Variables	**Total 1935-2015**	**WW2 1935-1945**	**BWS 1945-1971**	**Pre-UK EC 1971-1979**	**Post-UK EC 1979-1990**	**Pre-EMU 1990-1999**	**Post-EMU 1999-2015**
Macro-Finance							
Output	0.146**	0.981***	-0.244***	0.039	-0.078	-0.027	0.325***
Correlation	(0.032)	(0.134)	(0.029)	(0.057)	(0.052)	(0.057)	(0.118)
Yield Spread	0.223**	-2.484***	-0.313***	-0.117	0.184	1.128***	0.669**
Correlation	(0.184)	(0.496)	(0.068)	(0.154)	(0.145)	(0.214)	(0.301)
Inflation	0.336***	2.024***	-0.401***	-1.283***	0.356	-2.246***	-2.827***
Correlation	(0.122)	(0.339)	(0.101)	(0.413)	(0.273)	(0.304)	(0.441)
Foreign Exchange	0.245	-	-	0.332	0.603**	0.303	3.003***
Volatility	(0.284)	(-)	(-)	(0.509)	(0.294)	(0.379)	(0.858)
Gold Volatility	0.682***	-	-	0.723***	0.434***	0.514*	-0.008
	(0.130)	(-)	(-)	(0.146)	(0.137)	(0.267)	(0.370)
Oil Volatility	0.505***	-21.36**	0.136	0.313***	-0.180	0.640**	2.532***
	(0.116)	(9.725)	(0.156)	(0.111)	(0.211)	(0.251)	(0.394)
UK Recession	-0.007	0.227***	0.073***	-0.038	-0.230***	0.134***	0.547***
	(0.018)	(0.080)	(0.017)	(0.038)	(0.032)	(0.028)	(0.050)
US Recession	-0.033	0.682***	0.022	-0.130**	-0.007	0.400***	-0.291***
	(0.021)	(0.076)	(0.017)	(0.058)	(0.033)	(0.049)	(0.079)
Market Characteristics							
Stock Volatility	0.001	0.173***	-0.004	0.017***	-0.008	-0.046***	-0.059**
	(0.004)	(0.030)	(0.003)	(0.003)	(0.009)	(0.009)	(0.018)
UK Constituents	-0.086***	-0.249**	0.049***	0.091***	-0.084***	0.116***	0.025
	(0.018)	(0.101)	(0.012)	(0.022)	(0.015)	(0.021)	(0.021)
US Constituents	0.100***	-0.116**	0.074***	0.077**	-0.091***	-0.492***	-0.005
	(0.029)	(0.069)	(0.029)	(0.031)	(0.026)	(0.059)	(0.032)
Pol/Eco Episodes							
World War II	0.576***	0.709***	-	-	-	-	-
	(0.073)	(0.083)	(-)	(-)	(-)	(-)	(-)
Korean War	0.426***	-	0.179***	-	-	-	-
	(0.073)	(-)	(0.039)	(-)	(-)	(-)	(-)
Vietnam War	-0.356***	-	-0.273***	-	-	-	-
	(0.084)	(-)	(0.055)	(-)	(-)	(-)	(-)
Oil Shock 73/74	0.521***	-	-	0.189***	-	-	-
	(0.088)	(-)	(-)	(0.056)	(-)	(-)	(-)
1987 market crash	0.643***	-	-	-	0.482***	-	-
	(0.081)	(-)	(-)	(-)	(0.048)	(-)	(-)
Iraq-Kuwait War	0.482***	-	-	-	-	0.083	-
	(0.074)	(-)	(-)	(-)	(-)	(0.054)	(-)
EMS crisis	0.218***	-	-	-	-	-0.154***	-
	(0.074)	(-)	(-)	(-)	(-)	(0.038)	(-)
Mexican Crisis	0.043	-	-	-	-	-0.119***	-
	(0.074)	(-)	(-)	(-)	(-)	(0.035)	(-)
Asian and Russian	0.138*	-	-	-	-	0.091*	-
Crisis	(0.079)	(-)	(-)	(-)	(-)	(0.050)	(-)
Dot-com bubble	-0.002	-	-	-	-	0.333***	-
	(0.081)	(-)	(-)	(-)	(-)	(0.104)	(-)
Dot-com bust	0.128*	-	-	-	-	-	-0.175
	(0.072)	(-)	(-)	(-)	(-)	(-)	(0.108)
Afghanistan War	-0.299***	-	-	-	-	-	-0.006
	(0.107)	(-)	(-)	(-)	(-)	(-)	(0.153)
Iraq War	0.536***	-	-	-	-	-	-0.073
	(0.086)	(-)	(-)	(-)	(-)	(-)	(0.124)
Housing Bubble	-0.023	-	-	-	-	-	0.314**
	(0.094)	(-)	(-)	(-)	(-)	(-)	(0.133)
Global financial	0.024	-	-	-	-	-	0.311***
crisis	(0.059)	(-)	(-)	(-)	(-)	(-)	(0.077)
QE	-0.084	-	-	-	-	-	-0.096
	(0.109)	(-)	(-)	(-)	(-)	(-)	(0.161)
Eurozone debt	-0.175*	-	-	-	-	-	0.420***
crisis	(0.106)	(-)	(-)	(-)	(-)	(-)	(0.148)
Intercept	0.146***	-0.474***	0.115***	-0.013	0.144***	0.946***	0.222*
	(0.006)	(0.124)	(0.005)	(0.028)	(0.023)	(0.054)	(0.037)
Pseudo R^2	0.454	0.442	0.077	0.371	0.535	0.420	0.484

Notes: '*', '**' and '***' denote significant levels at 10%, 5% and 1%. Standard errors are in parenthesis.

2.6 Conclusions

In this chapter, we have examined the cross-market dynamics and the determinants of stock market integration between UK and US over the period 1935 - 2015. We provide novel explanations of the evolution of stock market integration by splitting the full sample into 6 structurally defined subsamples. Firstly, we examine the long- and short-run relationships between the two markets using cointegration analysis and vector error correction models. Our empirical estimates using several cointegration tests establish long-run equilibria between UK and US stock markets. We attribute stock market cointegration to possible international arbitrage, spillover effects and market contagion. Then, we find strong bidirectional return spillovers effects between the two markets, though US market leads the UK in price discovery in all the periods.

In line with few other studies, we use an asymmetric BEKK representation of a bivariate GARCH model to examine the volatility interdependence and spillovers between the UK and US markets (see Kroner and Ng, 1998). We find shock and asymmetric volatility spillovers are bidirectional, suggesting strong financial linkages between the two markets. Especially, the post-EMU period evinces the strongest bidirectional shock and volatility transmission, which suggests the existence of fundamental-based contagion. For instance, our results show that shocks originating in the US increase the volatility of UK stock market, while shocks originating in the UK decrease volatility in the US stock market. This confirms an established view that US stock market is the principal shock transmitter and crisis epicentre. Consequently, we model the impact of independent shocks on volatility of UK and US stock markets using Hafner and Herwatz (2006) volatility impulse response function. We find that the observed historical economic shocks increased observed volatility more in the UK stock market than the US, where the shocks had originated. This implies that the US market as a 'global centre' plays a domineering role in the transmission of shocks or macroeconomic news to UK and perhaps other international financial markets.

Further evidence shows stock market integration to be more time-varying and stronger in highly volatile periods. Particularly, the peaks in correlation coincide with specific episodes such as international monetary crisis in 1971, the October 1987 stock market crash, the 1998 Russian debt crisis, the 2008 global financial crisis and the recent Eurozone debt crisis. The unusual significant increases in correlation due to the occurrence of the aforementioned crises suggests some form of international financial contagion. We argue that the contagion effects in periods of economic and financial crisis may cause financial markets to integrate strongly even where convergence in macroeconomic fundamentals are weak. Moreover, the level of stock market integration between UK and US has grown significantly from an average of 0.138 in interwar/WW2 period to 0.574 in post-EMU period. We attribute such substantial increase to flexible exchange rate regime, market deregulation, financial liberalisation, macroeconomic policy convergence and the phase-in of European monetary union. The degree of shock transmission and correlation dynamics have important implications for financial market operators and policymakers.

For financial market operators, the increasing stock market integration and market efficiency require ingenuity in active portfolio management relating to speculative, arbitrage and hedging strategies. Indeed, the post-EMU period indicates that international investors are in a position to benefit less from portfolio diversification since returns from global stock markets are not cleared of volatility spillovers and contagion effects. However, investors may improve their diversification benefits by taking into account US past shock and volatility dynamics when forecasting volatility of UK stock returns as well as other assets' returns. We further ague that increasing stock market integration will engender timely portfolio management through efficient and accessible information, hence leaving international diversification benefits to more skilled investors. Since a number of macroeconomic and financial variables and a number of specific episodes are key determinants of integration, investors should rebalance their investment portfolio by taking care of such exogenous factors.

For policymakers, the stability of financial markets hinges more on building resistance to crisis spillovers and financial contagion, and effectively managing key macroeconomic fundamentals such as economic growth, interest rates, inflation and foreign exchange. Besides, if macroeconomic policies are inconsistent with the goal of financial stability, then it is expected that stock market integration will decline. As the evidence reveals that policy-making and regulatory framework is leading to macroeconomic convergence, improved capital market efficiency, cross-border investment, higher market liquidity and increased financial market depth, hence strengthening stock market integration between UK and US. Furthermore, the magnitude of a crisis and potential for contagion effects could be substantially mitigated by ensuring robust regulatory framework. The policymakers should be proactive by preventing irrational capital flows capable of reducing benefits to financial liberalisation through effective regulatory framework and sound public policy implementation. It is therefore imperative for policymakers to coordinate all these macroeconomic fundamentals in a manner that will reduce systematic market risk and maintain overall financial system stability.

Chapter 3. Investigating the Relationship between Portfolio diversification and Risk Management of Developed, Emerging and Frontier Equity Markets

3.1 Introduction

The growing interconnectedness and information flows across financial markets in the globe are raising serious challenges to investors seeking to maximise their returns while minimising risks with the right mix of assets. With the advancement of information and communication technology, there has been an increasing information spill over from one country to another arising from macroeconomic news announcements, structural reforms and unexpected episodes. Consider as an illustration, the transmission effects of domestic and global news have been connected to shocks and volatility spillovers across international financial markets (see for example, Kim *et al.* 2005; Panapoulou and Pantelidis, 2009; Singh *et al.* 2010; Bekaert *et al.*, 2014). The understanding of shock and volatility transmissions has important implications in a number of different areas such as asset pricing modelling, volatility forecasting, portfolio allocation and hedging performance.

Furthermore, the co-movement of financial asset returns is used as a measure of market integration. For instance, if UK stock market is less integrated with other stock markets, then international investors will benefit from risk-reduction through diversification. Theoretical and empirical literature have documented that increasing correlations among international financial markets will decrease diversification benefits (see for instance, Longin and Solnik, 1995; Driessen and Laeven, 2007; You and Daigler, 2010; Büttner and Hayo, 2011; Baur, 2012; Olson *et al.*, 2014). Similarly, a number of empirical studies have documented that correlation between international equity market returns is higher during crisis than during stable periods, hence dampening the gains from diversification for investors with standard expected utility preferences (see, among others, Erb *et al*., 1994; King *et al.*, 1994; Longin and Solnik, 2001; Ang and Bekaert, 2002; Antoniou *et al.*, 2007; Aslanidis *et al.*, 2010).

Recent studies have also shown increasing integration of European and non-European countries since the commencement of the European monetary union (see Baele, 2005; Kim *et al.*, 2005 Cappiello *et al.*, 2006; Savva *et al.* 2009; Büttner and Hayo, 2011). The implications of more integration and high level of volatility spillovers of financial markets may concomitantly reduce benefits that investors can reap from international diversification. For instance, if shocks originating from one market leads to increased volatility in the other markets, then the benefit of risk diversification is limited for an international investor.

Generally, investors are keen on optimising their portfolio wealth and will as a result engage in diversification strategies depending on their level of risk aversion. According to Dimitrious *et al.* (2013), the fall/rise in investors' appetite for risk will instantly reduce/increase their exposure to risky assets, hence the fall/rise in asset value concurrently. The dynamics of financial markets require that investors rebalance their asset portfolios from time to time in an increasingly evolving economic environment. Apparently, investors tend to weight their total asset portfolio disproportionately towards domestic assets and hence sacrifice the potential gains from international diversification. The tendency for the investor to hold more domestic assets in a diversified portfolio has been popularly referred to as *equity-home bias* and this behaviour has continued to puzzle many economists for several years.

Moreover, the information advantage at home induces investors to allocate a large share of their wealth to domestic assets and include foreign assets that can effectively hedge against domestic risk exposure. In other words, investors may be overexposed to aggregate shocks that could have been hedged by holding foreign assets. However, several theoretical explanations have been put forward as reasons for *equity-home bias*, including the role of exchange rate risk, explicit trading costs, risk aversion, country risk, and information asymmetries (see Gehring, 1993; Brennen and Cao, 1997; Coval and Moskovitz, 1999; Grinblatt and Keloharju, 2001). Apparently, as new information is incorporated by the market, it is expected that the riskiness of each individual assets changes. As a consequence, investors will seek to build a hedging strategy to diversify away the soaring risk in the domestic market through investing in other foreign markets. A number of important studies have addressed issues of hedging strategies across asset classes using risk-minimising hedge ratio (see Kroner and Sultan, 1993; Kroner and Ng, 1998; Olson *et al.,* 2014; Arouri *et al.,* 2015). Therefore, constructing dynamic optimal portfolio allocations and hedging effectiveness have substantial implications for strategic portfolio management.

For many financial analysts, the accuracy of financial risk measurement still portends a grave challenge. The effective use of risk management tools is crucial for mitigating growing market risk especially in periods of high uncertainty.[51] In spite of that, it is vital for investors that the estimation of market risk is accurate given the disastrous consequence of inaccurate measurement of risk on portfolio investment. In the last three decades, increasing financial market integration and globalisation have made risk measurement and management

[51] The risk of losses in positions resulting from movements in market prices is referred to as market risk.

complicated for many market participants. Despite these nuances, the use of financial risk management tools still has the capacity to measure and mitigate potential future losses in the midst of growing uncertainties.

One of the commonly used risk measurements is value-at-risk (VaR). It was first proposed by J.P. Morgan in 1994 as a measure of the market risk of daily trading positions. The VaR measure summarises the worst loss over a target horizon with a given level of confidence due to unfavourable movements in the market factors (see Duffie and Pan, 1997; Dowd, 1998; Jorion, 2001). Using VaR as a measure of risk will enable investors that trade in equity markets to have a holistic sense of the market risk profile. The VaR models are very much applicable to various financial data including the equity, bond, foreign exchange, commodity and derivative markets. The increasing use of VaR measures in portfolio trading has gained momentum in the last two decades and it is an effective decision-making weapon for diversification strategies. Given the popularity of VaR measures among market practitioners, the key challenge is to make a selection of VaR specifications that will accurately estimate the level of market risk of an asset portfolio holding.

Given this background, the aim of this chapter is to evaluate the nature of spillover effects, market integration, portfolio diversification and risk management between UK market and 29 foreign stock markets, spanning over Africa, Asia-Pacific, Europe and America. The period of analysis is significant because Europe has been through period of phenomenal monetary integration over the past 25 years, culminating in the birth of euro currency in 1999. The increasing integration of financial markets since the establishment of the European Monetary Union (EMU) in 1999 has important implications for risk management, portfolio diversification, policy-making and regulatory framework. Indeed, there have been several developments in the European Union (EU) in the last three decades that finally climaxed into the establishment of the EMU in 1999. Particularly, the structural shift in international financial architecture since the establishment of the euro has significantly impacted the global financial markets. We believe that UK's relationship with the rest of the world would have changed dramatically as a member of EU and non-member of EMU. Our selection of the UK stock market (FTSE100) as a benchmark country index against which all volatility transmission and correlation dynamics are modelled stems from the position of the UK as a leading global financial centre in the EU and second largest after the US.

Our choice of the period of study is considerably influenced by the prevalence of various political, economic and financial episodes. This justifies the use of risk management models for our empirical investigation on international portfolio diversification. The period started with the establishment of the euro currency in 1999, which indeed, changed the financial economic landscape not only in Europe but around the world. Thereafter, the new millennium was greeted with the dot-com bust between 2000 and 2002, but mainly affected the financial markets of many developed countries that experienced the dot-com bubble between 1998 and 2000. In 11th September 2001, the World Trade Centre in US was attacked by an international terrorist group, leading to the disruption of the financial markets for a short period. This turbulence caused a whopping investment portfolio loss of over $1.7 trillion. The aftermath of the attacks consequently led to the invasion of Afghanistan and Iraq by US and its allies in 2001 and 2003, respectively.

From mid-2003, many developed economies started experiencing financial market boom induced by the housing market bubble. This boom period was triggered mainly by the low official interest rate and inadequate regulatory oversight of the financial system. [52] Consequently, the action-reaction force played out in the financial markets after the housing bubble went bust in mid-2007, thereby leading to the global financial crisis and economic recession between 2007 and 2009. To avert another great depression, governments of various countries intervened through bail-outs, quantitative easing measures and other monetary and fiscal policy stimuli. These interventions provided capital and liquidity to the banking and financial systems that were at the verge of cataclysmic collapse, hence leading to a record low interest rate. While the intervention solved the crises in some countries, it triggered debt crisis in others, particularly in some Eurozone countries (Portugal, Ireland, Italy, Greece and Spain) from 2010, thereby slowing down the pace of global economic recovery.

The quantum of investment loss in major financial institutions during the recent global financial crisis is a further indication that poor portfolio management and defective risk management procedures could result in dire consequences for international investors. The stock market crash of 2008 revealed billions of dollars been wiped out from portfolio investment within few months. Prior to the crisis, the risk management models used by investment banks largely underestimated the probability of a widespread fall in house prices, particularly in the US and UK. Inevitably, when house prices did fall, it caused financial and economic devastation unprecedented since the Great depression. According to IMF (2009), the recessions that

[52] There was explosion of securitised products such as collateralised debt obligations (CDOs) and various types of mortgage-backed securities that were AAA rated by the leading rating agencies. These derivative products propelled the financial institutions to take on more risk by giving out loans to subprime borrowers.

originate from financial crisis are usually turbulent and economic recovery is always very weak. Indeed, the economic recovery has been really slow in most countries devastated by the great recession despite significant policy and regulatory reforms. Therefore, the issues of volatility transmission and portfolio management are very crucial to portfolio managers, financial analysts, regulators and policy-makers.

Since economies go through the cycles of boom and bust, and financial markets typify such cycles, we split the period under scrutiny into two subsamples, namely, 'Great Moderation (1999 - 2007)' and 'Great Austerity (2007 - 2015).' The Great Moderation (GM) period is characterised by macroeconomic stability, financial services boom and economic expansion whereas, the Great Austerity (GA) period is characterised by macroeconomic shocks, financial crisis, economic recession and sluggish economic recovery. [53] The analysis of two non-overlapping subsamples with approximately equivalent length is critical to understanding portfolio management in an evolving integrated markets. To the best of our knowledge, this study is the first to consider the uniqueness of these subsamples in comprehending the dynamics of financial integration and risk diversification.

Our rationale for selecting the GM and GA periods is to determine the impacts of different economic conditions on correlation measures, portfolio designs, hedging strategies and market risk. We focus in particular, on financial linkages and potential diversification benefits from the perspective of UK-based investors within the frame of the above two sub-periods, as aspect of the existing literature has so far been neglected by researchers. Our empirical findings to the following research questions would have significant implications for investors' portfolio allocation decisions and policy-makers' responses to the growing integrated and interdependent global financial markets.

We shall answer the following questions through empirical analysis;

1. Are there spillover effects between UK and foreign stock markets in the periods of Great Moderation and Great Austerity?
2. What impact does the degree of stock market integration between these markets has on international portfolio diversification benefits?
3. Is equity-home bias a feature in the dynamic asset allocation and hedging strategies of a UK investor?

[53] The former is characterised by a period of unprecedented macroeconomic stability while the latter is characterised by a period of macroeconomic instability.

4. Which VaR model delivers the optimal market risk quantification?

The motivation for this study is underpinned by evaluating the nature of shock and volatility transmissions, portfolio diversification benefits and performance of risk management framework in developed, emerging and frontier equity markets since the introduction of the Euro currency. The samples used are well diverse covering major stock markets in America, Africa, Asia-Pacific and Europe. Hence, generalisation and inferences can be made for the universe of developed, emerging and frontier markets from our findings. In contrast to substantial studies using US as a base country, we adopt the UK market as a base country in order to improve the scant literature of examining the impact of evolving stock market integration for portfolio diversification, dynamic hedging performance and tail risk from the context of more recent data, well diverse markets and robust methodologies. It is important to note that the capital city of UK, London is a global financial centre with well-developed financial architecture and systematically linked to other regional and national financial markets across the globe.

For tractability of analysis, we do not consider many important aspects of international diversification in order not to blur the focus of our study. For examples, we exclude aspect of transactions costs, exchange rate risk, inflation risk, country risk etc. This study is particularly useful to understanding correlation dynamics, portfolio diversification and risk management during the periods of tranquillity and turbulence.

Our study differs from previous studies and we contribute to the relevant literature in many respects;

1. Caporale *et al.* (2006) investigate the international volatility transmission across South East Asian, European, US and Japanese financial markets using bivariate BEKK model over the period 1986 - 2000. We broaden the analysis by evaluating transmission mechanism and correlation dynamics between UK and a large cohort of 29 stock markets using asymmetric bivariate BEKK model over the GM and GA periods. The study of volatility transmission is important because high level of volatility may diminish the potential benefits from international diversification.
2. Olson *et al.* (2014) use the GARCH-BEKK model to analyse dynamic correlations and hedge ratios for energy/S&P 500 portfolio from 2000 to 2011. We extend the analysis by using asymmetric BEKK model to examine the time-varying optimal portfolio weights and dynamic hedge ratios of UK/foreign stock portfolio holdings from 1999 to

2015. To our knowledge, no study has used more recent dataset to examine dynamic portfolio allocation and hedging performance from the perspective of a UK investor.

3. Recent studies on VaR have focused on the bull and bear markets based on limited number of countries (see You and Daigler, 2010). We use an extensive dataset by quantifying the optimal market risk of diversified stock portfolios using VaR models over the tranquil and volatile periods.
4. Dimitrakopoulos *et al.* (2010) consider the issue of backtesting of VaR estimates for the period of post-Asian, Mexican and Russian financial crisis. We apply backtesting procedures on VaR forecasts of optimal market risk in developed, emerging and frontier equity markets.

Our empirical results suggest the following;

(1) there is significant evidence of shock and asymmetric volatility spillovers between UK and other foreign markets. These spillover effects are stronger between UK and developed markets and weaker between UK and frontier markets. In fact, they are more severe in the GA period, suggesting that transmission mechanisms are more pronounced during turbulent period than tranquil times. Similarly, asymmetries play an important role in driving the dynamics of conditional variance and correlation between UK and developed markets than between UK and emerging/frontier markets. The strong financial linkages between UK and developed markets suggest that increasing market integration, higher degree of financial openness and cross-border market contagion play crucial role in the transmission process.

(2) there is substantial variation of positive correlation and the increasing integration suggests reduction in diversification benefits for UK investors. The increase in correlation is considerably higher during the GA period suggesting that period of crisis leads to increasing stock market integration. The UK market is strongly linked with developed markets, especially European markets, moderately linked with emerging markets and weakly linked with frontier markets, particularly Sub-Saharan African and South-Asian markets. This further suggests that UK investors may benefit from risk-return trade-off by constructing portfolio that would have a mix of stocks from emerging and frontier markets.

(3) on the basis of two-asset portfolio allocation, the optimal portfolio holding allocated over 50% weight to UK assets in 21 out of 29 diversified portfolios during GM period and 20 out of 29 diversified portfolios during GA period. The equity home-bias largely

exercised by UK investors can be ascribed to factors such as asymmetric information, risk aversion and hedging strategy due to country risk. We also find that the frontier markets provide the best hedging performance to hedge UK stock movements, followed by emerging and developed equity markets, respectively. The hedging benefits are stronger in period of extreme downturns, suggesting the usefulness of foreign stock market as a sound hedging instrument for UK stock market in crisis periods.

(4) the VaR analysis indicates higher risk of loss of UK investors diversifying into European markets and lower risk of loss diversifying into North American markets. In addition, diversifying into emerging sub-Saharan African and South-Asian frontier markets has lower tail risk in periods of GM and GA. For most diversified portfolios, the EWMA and GARCH models produce high risk of investment loss during GM period while the MA and HS models generate higher risk of investment loss during GA period. We argue that perhaps due to the high sensitivity to changes in volatility, the latter models may overestimate risk diversification in crisis periods, whereas due to sharp adjustment to changes in volatility, the former models may underestimate risk diversification in crisis period. Comparing the four competing models, the skewed GARCH-*t* model properly evaluates market risk at 5% VaR level, whereas the MA model has the best forecasting performance at 1% VaR level for all markets in GM and GA periods. This suggests that tail behaviour using GARCH and MA models should be critically considered to properly assess the market risk in international portfolio diversification.

The remainder of the chapter is structured as follows. Section 3.2 reviews the literature on market integration, portfolio diversification and risk management. Section 3.3 evaluates the methodologies used to estimate spillover effects, time-varying correlation coefficients, optimal portfolio weights, hedging ratios and value-at-risk. Section 3.4 describes the data and reports some preliminary statistics. Section 3.5 sets out the empirical results and discusses some implications. Section 3.6 summarizes and concludes the chapter.

3.2 Literature Review

Previous studies have examined stock market integration from the perspective of volatility spillover effects and time-varying conditional correlations. We investigate the linkages between integration, portfolio diversification and risk management of a wide array of stock markets obtained from the Morgan Stanley Capital International (MSCI) classification of countries into developed, emerging and frontier markets.

This chapter begins in section 3.2.1 with description of the features of developed, emerging and frontier markets. In section 3.2.2, we describe the historical development of VaR as a useful tool in risk management. The empirical literature on stock market integration and portfolio diversification is provided in section 3.2.3. Finally, we illustrate the empirical literature on tail risk analysis in section 3.2.4.

3.2.1 *Description of Financial Markets*

A financial market is described as a marketplace where prospective buyers and sellers engage in the trading of financial assets such as stocks, bonds, currencies, commodities and derivatives. The prices of securities are determined by market forces and basic regulations on trading, costs and fees are applicable to all market participants. Financial markets exist in almost every country in the world and can be classified into developed and developing markets (emerging and frontier markets). In the last three decades, the financial markets around the world have experienced revolutionary changes attributed to factors such as privatisation of state-owned enterprises, economic deregulation, financial liberalisation, influence of stock exchanges, foreign ownership of assets and liabilities, improved macroeconomic environment, growth of multinational corporations, cross-border capital flows, cross-listing of stocks, improved institutional framework of investors, and advancement in information and communication technology.

In order to understand the risk-return profile of a portfolio, many investors evaluate the political and economic structure of countries when considering their investment strategy. Unlike domestic investors, international investors are faced with exchange rate risk, capital flow restrictions, country-specific regulations, economic and political risks when constructing their investment portfolio. However, international investors consider political risk factors (government stability, regulatory quality, corruption, socioeconomic conditions, democratic accountability, state fragility, law and order), as well as financial and economic risk factors (debt profile, current account balance, exchange rate stability, GDP per capita, real annual GDP growth, inflation rate, budget balance).

Despite the opportunities offered by international investing, individual and institutional investors' tend to allocate their asset portfolio disproportionately towards domestic assets even though there are no regulatory restrictions on cross-border asset holding. The tendency to hold more domestic assets is commonly referred to as *home-country bias puzzle* (see, French and Porteba, 1991; Cooper and Kaplanis, 1994, Tesar and Werner, 1995; Driessen and Laeven 2007). It follows that the evidence on portfolio diversification has been classified under two strands of literature. The first strand of literature favours significant international diversification benefits or diminished home bias in equities (see for example, Amadi, 2004; Speidell and Khrone, 2007; Cheng *et al.*, 2009; Gupta and Donleavy, 2009; Berger *et al.*, 2011; Coeurdacier and Guibaud, 2011). Another strand supports limited or insignificant diversification benefits or diminishing home bias over time (see Guidolin and Hyde, 2008; You and Diagler, 2010).

A. Developed Markets

The developed market is characterised by a strong and active large-sized non-bank financial sector consisting of money market, stock market, bond market, derivative market, currency market and commodity market. These markets are considered to have greater financial openness, highly liquid and more diversified. They also have minimum restrictions on foreign ownership of assets and liabilities, well-functioning financial system and better integrated with world financial markets. The rapid development of the financial markets has further reduced transaction and information costs over time. These have contributed to growing interlinkages across developed markets, hence limiting the potential benefits of diversification. There is a growing evidence of increasing stock market integration among the major developed countries (see, Brooks and Del Negro, 2004; Kizys and Pierdzioch, 2009; Burchi and Martelli, 2016).

In the last two decades, the developed countries have been experiencing ageing population, low growth rate, rising debt, high current account deficit and burgeoning social cost. Recently, the US sub-prime mortgage crisis that culminated into global financial crisis between 2007 and 2009 badly affected many developed markets. Subsequently, the Euro area plunged into a sovereign debt crisis, hence global economic recovery has been sluggish since the end of the Great Recession in 2009. As a consequence, the lack of economic reforms, burgeoning budget deficit and overall economic mismanagement caused the prolonged Eurozone debt crisis, of which Portugal, Ireland, Italy, Greece and Spain (PIIGS) have been severely hit. Despite the stock market recovery but limited growth potential, investors are unlikely to reap substantial return on investment when compared with the faster-growing emerging and frontier markets.

The majority of countries in Western Europe have a well-developed markets and have strongly integrated economies, particularly for Eurozone countries because of the use of a single currency. Generally, portfolio diversification benefits are gradually eroding in mature markets, thereby shifting the focus of researchers and market practitioners to emerging and frontier markets.

B. Emerging Markets

The emerging markets have some characteristics of the developed markets, although they fall into the low to middle income per capita category and are less informationally efficient. According to Pretorious (2002), emerging stock market can be described as market in transition in terms of increasing size, activity or level of sophistication. The spate of financial liberalisation in the 1980s and 1990s among countries in Asia, Latin America, Eastern Europe and Africa have placed some of them to attain the status of emerging markets. The deliberate government policy of establishing strong financial institutions had triggered the pace of financial development in the emerging markets. The economic progress in these countries has actually stimulated an expansion of the financial system as well. The increase in per capita income of these countries may induce international investors to diversify their investments into these fast growing economies.

It is generally believed that the emerging economies have overtaken the developed economies as the engine of world growth. As a result of this, increasing number of institutional investors considers the emerging markets as an integral part of their stock portfolio allocations. In the last two decades, investors have discovered the benefit of diversification in the emerging markets as a way of enhancing returns and potentially minimising portfolio risk.

Furthermore, the more established emerging markets that formed the BRICS nations (Brazil, Russia, India, China and South Africa) are characterised by having a better fiscal accounts, trade balances and growth prospects than their counterparts in the developed countries. For instance, Russia is the largest established emerging markets in Eastern Europe, Brazilian economy has become strong despite relatively high interest rates and China has become the second largest economy in the globe. However, many investors are still wary of the level of default on sovereign debts and economic policies of some emerging markets. The emerging market catch-up to a developed market status may not hold soon due to regulatory bottlenecks, unsustainable debt levels and regressive economic policies. Given the global outlook of most emerging markets, they are gradually having common trends with the developed markets, hence diminishing their opportunities for portfolio diversification. Since market practitioners aim at recovering or preventing lost diversification benefits, attention in recent years is gradually shifting to the frontier markets.

C. Frontier Markets

The frontier market is described as an underdeveloped market with features which include lower market capitalisation, less accessibility, less transparency, restricted foreign ownership, poor regulation, lower standard of corporate governance, inadequate financial reporting, less competition, high transaction costs, low liquidity and high volatility. In spite of that, the market is still investable in the developing world and the market represent approximately 0.2% of the total global equity investment opportunity set. These frontier markets are located in South Asia, Central and South America, Eastern Europe, the Middle East and North Africa and sub-Saharan Africa. In recent times, frontier market countries appear to be one of the fastest growing economies in the world with abundant natural resources for future development.

Despite the challenging political and economic environments of these markets, there have been incremental financial and economic reforms since the mid-1990s that are paving way for portfolio investments in these markets. It is important to note that these markets are still highly vulnerable to shifts in global trends, macroeconomic shocks and fragile politically. The frontier market economies are not as integrated into global markets, and they are subject to a wide range of idiosyncratic local economic and political dynamics (Morillo, 2012).

However, the last decade of many of these markets has recorded rising real per capita GDP, declining inflation, stabilising currency exchange rates, burgeoning corporate profits, increasing openness to and accessibility for foreign investors and relatively higher return on investments in these markets. Graham and Emid (2013) argue that frontier market economies are at a stage of development where the emerging markets were 10 to 15 years ago, and it is highly probable that they will trail the path of economic development as the emerging markets. As these markets continue to grow in all ramifications, they will certainly join the rank of emerging markets in the foreseeable future while perhaps some emerging markets would take a leap forward to be classified as developed markets.

In summary, international investors may diversify their investment portfolios to mitigate high exposure to risk in different markets. Figure 3.1 shows that MSCI developed, emerging and frontier markets exhibit similar trends in period of economic upturns and downturns. In particular, the 2008 stock market crash is evident in the sudden downward trends in these markets. The diagram further demonstrates moderate fluctuations in stock prices during the period of 'Great Moderation' and the turbulent stock price movements during the period of 'Great Austerity'. For rational investors seeking to optimise their risk-return profile, international diversification with a mix of developed, emerging and frontier portfolios will be given careful consideration.

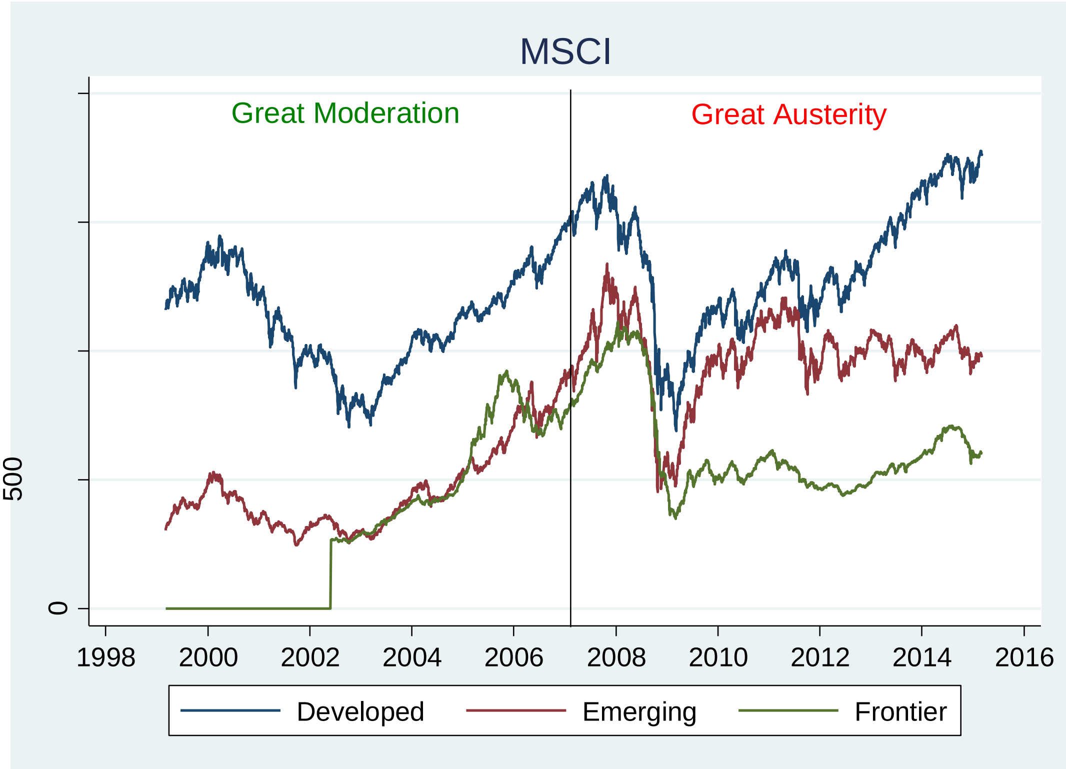


Figure 3.1: Stock Prices for MSCI Developed, Emerging and Frontier Markets

3.2.2 *Value at Risk*

After the wave of financial market deregulation in the 1980s and 1990s, financial institutions became more exposed to market risk. The threat to financial market stability as a result of greater exposure to risk informed the Basel Accord in 1996, which allows both the use of standardised and bespoke models for measuring market risk. Fundamentally, Basel III requires financial institutions to set aside certain amount of capital and liquidity due to market risk, credit risk and liquidity risk.

The frequently used measures of risk by investors include VaR and expected shortfall (ES). These measures of risk have been extensively used to evaluate risk management strategies. Potentially, investment risk exists when investors make decisions about the future based on known probabilities. The VaR model was developed by J.P. Morgan in 1995, of which volatility is a key input. The use of volatility is central for measuring risk and making an accurate choice of volatility model is one of the most crucial elements in determining the effectiveness of VaR.

Furthermore, VaR is popularly used by financial institutions, regulators, investors and risk managers to quantify and manage market risk. Particularly, banks are increasingly compelled by regulators to gauge their market risk using best-suited risk measurement model. The widespread use of VaR has led many financial institutions to adopt the principle of VaR-based risk disclosure in their annual reports for the benefit of stakeholders

In addition, VaR measures the downside “tail risk” of investments but there is no general standard of VaR measurement given the ubiquitous parametric, semi-parametric and non-parametric models. VaR quantification is desirable because it considers the whole distribution and has become popular among market practitioners. The use of VaR has fanned the wave of research since the 1996 Basel Accord.

The inability of VaR measure to capture losses beyond the VaR level led to the development of ES (also called tail VaR) by Artzner *et al*. (1999). Comparing VaR with ES, Yamai and Yoshiba (2005) argue the use of single risk measure should not dominate financial risk management and therefore complementing VaR with ES represents an effective way to provide more comprehensive risk monitoring. However, Artzner *et al*. (1999) posit that ES is more reliable to measure risk under market stress than VaR but it is estimated with more uncertainty than the latter. On the contrary, Ronn *et al.* (2009) argue that VaR measures are more accurate when applied to more volatile market periods. To capture tail fatness in the extreme tails of distributions, Embrechts *et al.*, (1997) develop the extreme value theory (see also McNeil and Frey, 2000; Diebold, 2012). EVT focuses on the behaviour of extreme outcomes, hence, the application is less useful when extreme observations are limited to estimate the quantities of interest.

The literature on risk measures using VaR has substantially focused on using non-parametric (historical simulation and its variants etc.), semi-parametric approach (EVT, CAViaR etc.) and parametric models (e.g. moving average, RiskMetrics, realised volatility model, switching volatility regime model, ARCH-type models, GARCH-type models etc.). The risk of choosing inappropriate model, which is referred to as “model risk” is prevalent in VaR measurement. The model risk is being tackled by risk analysts using backtesting procedures. Recently, market risk has been heightened by series of unexpected events, and therefore selecting appropriate tail risk measurements to assess the level of investment loss that can be tolerated is crucial in portfolio investment decisions.

3.2.3 Empirical Evidence on Stock market integration and Portfolio Diversification

The principle of diversification was formally developed in modern portfolio theory by Markowitz (1952, 1959). The diversification principle is popularly used in finance as a process in which investors tend to substantially reduce investment risk without significantly impacting portfolio returns. One of the earliest paper by Grubel (1968) suggests that by including foreign securities, investors who diversified portfolio internationally are able to realize a lower variance in returns because of the less than perfect correlation amongst distinct stock markets across the globe (see also Elton *et al.* 1995).

Many naïve investors have a common dictum that says 'do not put all your eggs in the same basket' and as a result randomly choose unrelated assets to derive benefits from diversification. This strategy has been termed naïve diversification strategy. An investor would ordinarily invest substantially in domestic assets no matter the level of restrictions removed from trading in foreign assets. The preference to domestic assets by local investors has been termed 'home-bias' of financial assets (see, French and Poterba, 1991; Lewis, 1996; Coval and Moskowitz, 1999). Perhaps, the home-bias exercised by investors can be attributed to factors such as risk aversion, asymmetric information, exchange rate risk, transaction costs, capital gain tax, regulatory bottlenecks and country risk.

Empirical literature on international market integration and diversification has focused more on developed and emerging markets. Previous studies, most notably Solnik (1974), finds that international diversification is favourable on the premise of cross-market correlations. Similarly, Odier and Solnik (1993) find that international diversification is still profitable even in an increasing information integration across markets, particularly in volatile periods.

Kroner and Ng (1998) apply the asymmetric dynamic covariance matrix model derived from four multivariate GARCH models (VECH, BEKK, FARCH and CCORR) to examining the dynamic relation between large- and small-firm returns. They find that large-firm returns can affect the volatility of small-firm returns whereas, small-firm returns have less effect on large-firm volatility. They also show that bad news emanating from large firms can cause volatility in both small- and large-firm returns. Finally, they evince that correlations between the risk-minimising hedge ratios derived from the multivariate volatility models are low and occasionally, negative. Also, Ang and Bekaert (2002) employing a dynamic international asset allocation model with regime switching, and find that the returns of US, UK and German equities are more highly correlated during bear markets.

Furthermore, the extensive literature on international portfolio diversification is based typically from the perspective of US investors (see Bekaert and Urias, 1996; DeRoon *et al.,* 2001; Li *et al.*, 2003; Chiou *et al.,* 2009). However, few other literature based their analysis from the perspective of other developed markets. For instance, Fletcher and Marshall (2005) investigate the diversification benefits for UK investors from January 1985 to December 2000. They find significant increases in the Sharpe ratio by including either global industry or country equity portfolios to a domestic asset allocation strategy even in the presence of short selling constraints.

Driessen and Laeven (2007) study how the diversification benefits vary across 52 countries from the perspective of a local investor. First, they find substantial regional and global diversification benefits for domestic investors in both developed and developing countries. Second, they discover that diversification benefits are larger for developing countries compared to developed countries. They conclude that the decline in country risk over time has decreased diversification benefits from 1985 to 2002.

Using DCC GARCH, Antoniou *et al.* (2007) find that conditional correlation increased during the bear markets and fall during recovery periods between European and US markets. Similarly, Meric *et al.* (2008) apply principal components analysis and Granger causality to investigate the portfolio diversification implications of the co-movement of sector indices during the bull and bear markets in the US, UK, German, French and Japanese stock markets. They find that in a bear market, country diversification opportunities are limited, whereas in a bull market, investors can derive more benefit from international diversification.

Panopoulou and Pantelidis (2009) study the international information transmission between the US and the rest of the G-7 countries using BEKK model from 1985 to 2004. They find increased interdependence in the volatility of the markets under examination. Jayasuriya and Shambora (2009) investigate diversification benefits across market classifications and consider optimal portfolios of developed, emerging and frontier markets. They find that there is improved portfolio risk and returns when investors diversify their portfolio into six frontier markets.

Coeurdacier and Guiband (2011) investigate whether investors accurately hedged their over-exposure to domestic risk by investing in foreign stock markets that have low correlation with their domestic stock market. They find that investors do tilt their foreign holdings towards countries which offer better diversification benefits. Berger *et al.* (2011) use the principal components analysis to examine frontier market equities with respect to world market integration and diversification. They find that frontier markets have low integration with the world market and thereby offer significant diversification benefit.

Mensi *et al.* (2013) employ a VAR-GARCH to examine the return links and volatility transmission between the S&P 500 and commodity prices (energy, food, gold and beverages) over the turbulent period from 2000 to 2011. They find significant correlation and volatility across commodity and equity markets. They also examine the optimal weights and hedge ratios for commodity-stock portfolio holdings and find that adding commodities to a stock-diversified portfolio, improve its overall risk-adjusted return performance.

Olson *et al.* (2014) investigate the relationship between the energy and equity markets using multivariate BEKK model from 1985 to 2013. They find that low S&P 500 returns cause significant increases in the volatility of the energy index and energy volatility is sensitive to equity returns shocks. According to their findings, conditional correlation and hedge ratios increased in period of global financial crisis. They argue that the dynamic hedge ratio analysis suggests that the energy index may not be a good hedging instrument.

In summary, past diversification studies gave less attention on exploring international diversification benefits and effective risk management strategies from the perspective of the UK market. Many findings have shown increasing integration in crisis than non-crisis periods, hence, diminishing gains from portfolio diversification. Apparently, changing economic conditions should imply time variation in correlation, portfolio weights and hedge ratios across international stock markets. Similarly, the increasing level of financial market integration limits the opportunities derivable from diversification but we cannot rule out home-bias phenomenon that characterises many investors' behaviour. Therefore, our study will focus on investigating time variation in volatility, correlation, portfolio weight and hedge ratio from the perspective of a UK investor given the scant empirical literature in this area of international diversification study.

3.2.4 Empirical Evidence on Tail Risk Analysis

Focusing on recent tail risk analysis, Giot and Laurent (2004) gauge the forecasting ability of VaR models by using realized volatility and skewed Student APARCH model for 2 stock indexes (CAC and S&P500) and 2 exchange rates (the YEN-USD and DEM-USD). They find the ARCH type models and realised volatility can deliver accurate VaR forecasts. Similarly, So and Yu (2006) investigate the VaR forecasting performance of seven GARCH models against the RiskMetrics models for 12 equity market indices. They find that both stationary and fractionally integrated GARCH models outperform RiskMetrics in estimating 1% VaR. They also discover that asymmetric behaviour in the equity market data that *t*-error models present better 1% VaR estimates than normal-error models in the long position, but not in short position.

Maghyereh and Al-Zoubi (2006) examine VaR and EVT on 7 MENA countries using variance-covariance method, historical simulation and ARCH-type process with normal distribution, student-*t* distribution and skewed student-*t* distribution. They find that the asymmetric power ARCH and the extreme value are the dominant methods for the estimation of VaR.

Kuester *et al.* (2006) investigate new models for predicting VaR in a univariate context on the NASDAQ composite index. They find that combining a heavy-tailed GARCH filter with an EVT approach performs best overall, followed by filtered historical simulation and heteroskedastic mixture distributions.

Bao *et al*. (2006) evaluate the predictive performance of VaR models in 5 emerging markets (Indonesia, Korea, Malaysia, Taiwan and Thailand) during the Asian financial turmoil. They find that RiskMetrics model behaves reasonable well in tranquil periods (before and after the crisis) and some extreme value theory models do better in the crisis period, while parametric Student's-*t* specifications outperform normality based approaches for the higher quantiles.

McMillan and Kambouroudis (2009) examine the forecasting performance of RiskMetrics and GARCH models in 31 stock markets. They find that when forecasting the 1% VaR, the APARCH (asymmetric-power GARCH) model perform far better than the RiskMetrics model while at 5% VaR, the RiskMetrics model is adequate. They conclude that the RiskMetrics only performs well in forecasting the volatility of small emerging markets at 5% VaR measure.

Assaf (2009) examines the tail measures and VaR for four emerging markets (Egypt, Jordan, Morocco and Turkey). He finds that the VaR estimates based on the tail index are higher than those based on normal distribution for all markets and therefore conclude that accurate risk assessment should not neglect the tail behaviour in these markets in order to avoid improper measurement of market risk.

Dimitrakopoulos *et al.* (2010) investigate VaR, EVT and adaptive filtered models during normal, crisis and post-crisis periods of Asian, Mexican and Russian financial crises from 1995 – 2003 in 16 emerging and 4 developed stock markets. They find that performance of the parametric (non-parametric) VaR models is enhanced (worsened) during post-crises periods due to the inclusion of extreme event in the estimation sample. They argue that VaR measure effectively captures losses in normal market but fared badly in extremely volatile situations.

You and Daigler (2010) examine the weekly prices for the world's most active stock index futures contracts using four-moment value at risk (VaR) from 1997 – 2002. They find that there is diminished benefits from diversification arising from the increasing positive trend overtime in the time-varying correlation between the US and European markets. Employing the modified VaR, they find that there is little benefit in diversifying from the S&P 500 index to the world index, or to the markets in one other continent. Finally, analysis of trade-offs between the moments suggest a positive relation between standard deviation and skewness, and between standard deviation and excess kurtosis, and a negative relation between correlation and risk.

Chkili *et al.* (2012) use univariate and multivariate GARCH-type models to examine the empirical relationships between stock returns (CAC40, DAX and FTSE100) and exchange rates (USD/EUR and USD/GBP) over the period 1999 to 2009. They find the suitability of FIA-PARCH model in forecasting portfolio's market risk exposure and the existence of diversification benefits between these markets.

In summary, the empirical evidence on linking portfolio diversification with VaR is still scant. In practical terms, a growing number of international investors are evaluating investment portfolio based on downside risk. Few empirical studies have used VaR as a measure of downside risk in bear and bull periods of a single portfolio. However, we are yet to find studies that incorporate optimal portfolio weights to quantify VaR of a two-asset portfolio in stable and turbulent periods. This will however be considered in our empirical analysis.

3.3 Methodology

In section 3.3.1, we set out the ASY BEKK model for investigating spillover effects and correlation dynamics. The equations for estimating the risk-minimising portfolio weights and hedge ratios are described in section 3.3.2. The VaR models considered, including historical simulation (HS), moving average (MA), RiskMetrics (EWMA) and skewed GARCH-*t* models are explained in section 3.3.3. These models are commonly used in the investment community for volatility forecasting and portfolio management. Finally, we discuss back-testing procedures based on the forecasting performance of the markets under scrutiny in section 3.3.4.

3.3.1 *Asymmetric BEKK-GARCH Model*

The modelling of volatility is fundamental to understanding market integration and risk management. In order to capture the international transmission of stock returns' volatility, we use the asymmetric (ASY) BEKK (Baba, Engle, Kroner and Kraft) model. The model was proposed by Kroner and Ng (1998) and it allows for asymmetric effects of positive and negative shocks on both variance and covariance.[54] The asymmetric effect in volatility is caused by a rise in the information flow following negative shocks i.e. bad news, and should therefore affect the covariance between stock index returns because of the effect of a change in the relative rate of information flow across financial markets. The model guarantees positive semi-definiteness by working with quadratic forms which thereby give it an advantage over the VECH model.

The two-dimensional vector of stock returns (R_t) for the UK and US markets can be expressed in the form

$$R_t = \alpha + u_t, \; t = 1, 2, \ldots, T \tag{3.1}$$

where the parameter of the return equation is defined by the constant $\alpha = (\alpha_1, \alpha_2)$; the residual vector $u_t = (\varepsilon_{1,t}, \varepsilon_{2,t})$ is bivariate and normally distributed $u_t \mid I_{t-1}(0, H_t)$, with its corresponding time-varying conditional covariances of the shocks given by;

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{pmatrix} \tag{3.2}$$

The parameter matrices for the variance equation (3.2) are defined as *C*, which is restricted to be upper triangular, and two unrestricted matrices, *A*, *B* and *D*.

[54] The asymmetric responses of volatility indicate that stock volatility tends to rise more in response to negative shocks than positive shocks. In other words, volatility reacts asymmetrically to positive and negative return shocks (see, Nelson 1991, Engle and Ng, 1993)

The two-asset (bivariate), one-lag BEKK model is defined as;

$$H_t = CC' + A'\, \varepsilon_{t-1}\varepsilon'_{t-1}\mathrm{A} + B'H_{t-1}B + D'\eta_{t-1}\eta'_{t-1}D \tag{3.3}$$

The conditional variance-covariance model (H_t) for the two-variable case are given in this matrix specification as;

$$h_{11,t} = c_{11} + \left(\alpha_{11}^2\varepsilon_{11,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1}\right) + \left(\delta_{11}^2\eta_{11,t-1}^2 + 2\delta_{11}\delta_{21}\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}^2\eta_{22,t-1}^2\right) \tag{3.4}$$

$$h_{22,t} = c_{22} + \left(\alpha_{12}^2\varepsilon_{11,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{22}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1}\right) + \left(\delta_{12}^2\eta_{11,t-1}^2 + 2\delta_{12}\delta_{22}\eta_{11,t-1}\eta_{22,t-1} + \delta_{22}^2\eta_{22,t-1}^2\right) \tag{3.5}$$

$$h_{12,t} = c_{12} + \left(\alpha_{11}\alpha_{12}\varepsilon_{11,t-1}^2 + (\alpha_{21}\alpha_{12} + \alpha_{11}\alpha_{22})\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}\alpha_{11}\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}\beta_{12}h_{11,t-1} + (\beta_{21}\beta_{12}+\beta_{11}\beta_{22})h_{12,t-1} + \beta_{21}\beta_{22}h_{22,t-1}\right) + \left(\delta_{12}\delta_{22}\eta_{11,t-1}^2 + (\delta_{21}\delta_{12} + \delta_{11}\delta_{22})\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}\delta_{22}\eta_{22,t-1}^2\right) \tag{3.6}$$

where $h_{11,t}$ and $h_{22,t}$ are conditional variances at time *t* of UK and foreign stock indices, respectively. The conditional covariance between the UK and foreign stock indices at time *t* is indicated by $h_{12,t}$. ε_{t-1} is the vector of errors from previous period. *A, B, C* and *D* are all (*2 x 2*) parameter matrices. The diagonal and non-diagonal parameters capture own-market volatility (H_{t-1}) and cross-market volatility ($\varepsilon_{t-1,1}^2, \varepsilon_{t-1,2}^2$) shocks across markets over time. The parameters of matrix *D* capture the magnitude of asymmetry of volatility effect such that the term η_{t-1} takes the value *1* for negative shocks and *0* otherwise (that is, $\eta_{t-1} = 1$ when $\varepsilon_{t-1} < 0$ and $\eta_{t-1} = 0$ when $\varepsilon_{t-1} \geq 0$). [55]

The diagonal parameters in matrices *A* and *B* measure the effects of own past shocks and past volatility of market *i* on its conditional variance, while the diagonal parameters in matrix *D* measure the response of market *i* to its own past negative shocks. The off-diagonal parameters in matrices *A* and *B* capture the cross-market volatility effect, while the off-diagonal for *D* measure the response of market *i* to the negative shocks of market *j*, which represent the cross-market asymmetric effects. The statistical significance of the coefficients attached to lagged variances, covariances and error terms are estimated using the **delta method** since they consist of non-linear function of the rudimentary parameters. [56] This model has been extensively used

[55] The diagonal elements in matrix A capture the own ARCH effect, the diagonal elements in matrix B capture the own GARCH effect and the diagonal elements in matrix D capture the own asymmetric effect.

[56] This approximation involve the use of a Taylor series expansion expressed in a polynomial approximation in order to obtain the variance or random variables in non-linear functions. For instance, $h_{11,t-1}$ in a bivariate

to detect the presence of spillover effects in a bivariate or multivariate framework (see Caporale *et al*., 2006; Panopoulou and Pantelidis, 2009; Arouri *et al.*, 2015).

We compute the conditional correlation by using the conditional variances and covariances obtained from the ASY BEKK model;

$$\rho_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t} \cdot h_{22,t}}} \tag{3.7}$$

where $\rho_{12,t}$ is the estimated time-varying conditional correlation between UK and foreign stock markets; $h_{11,t}$ and $h_{22,t}$ are the conditional variances for UK and foreign stock markets, respectively. The conditional covariance is denoted as $h_{12,t}$. The maximum likelihood method is employed to estimate the elementary parameters of the student-*t* ASY BEKK model.

3.3.2 *Portfolio Weights and Hedge Ratios*

The accurate measurement of time-varying conditional variance and covariance is crucial for portfolio diversification and risk management. We suppose that a UK investor is holding a FTSE100 index and wishes to hedge his stock position against adverse price movements by investing in foreign stock index. Practically, the objective of an investor is to minimise the risk of UK-foreign stock portfolio while keeping the same expected returns. To this end, we follow the analysis of Kroner and Sultan (1993) and Kroner and Ng (1998) by estimating the portfolio weights and hedge ratios using the variances and covariances obtained from the ASY GARCH-BEKK (*1,1*) model. The optimal portfolio weight of UK stock index is given by;

$$w_t^{12} = \frac{h_t^2 - h_t^{12}}{h_t^1 - 2h_t^{12} + h_t^2} \tag{3.8}$$

The following constraints on the optimal weight of UK stock index is imposed on the mean-variance portfolio optimisation approach if short selling is prohibited:

$$w_t^{12} = \begin{cases} 0 \; if \; w_t^{12} < 0 \\ w_t^{12} \; if \; 0 \le w_t^{12} \le 1 \\ 1 \; if \; w_t^{12} > 1 \end{cases} \tag{3.9}$$

where w_t^{12} is the weight of UK stock index in £1.00 of two assets (UK and foreign stock indices) at time *t*. The term h_t^{12} represents the conditional covariance between the UK and

GARCH BEKK could be modelled as *var(h(θ))* $\approx \left(\frac{\partial h}{\partial \theta}\right)^2$ *var(θ).* Where θ represents the estimated parameter, such as $\beta_{11}, \beta_{12} \; or \; \beta_{13}$. As a consequence, it requires the derivative of $h_{11,t}$ with respect to the estimated variable θ and the variance of θ.

foreign stock indices at time *t*. The optimal weight of foreign stock index in the portfolio holding is 1 - w_t^{12}.

Since the objective of a UK investor is to optimally hedge the risk of investment in UK stock market, then it is required that a proper position on the foreign stock market is taken to minimise the risk of the hedged position.[57] In other words, the foreign stock portfolio is used to hedge against UK stock return volatility. To minimise the risk of a portfolio, a long position (buying) of £1.00 in the UK stock market can be hedged by a short position (selling) of $£\beta_t$ in the foreign stock market. A short position in the foreign stock market is appropriate because the UK investor already owns the domestic asset and expects to sell it at some time in the future. The intuition behind this is that when market price goes up, a short hedge eliminates (reduces) risk due to the gain made in the domestic stock market being offset by the loss realised in the foreign stock market. In contrast, when market price goes down, a short hedge eliminates (reduces) risk associated with the loss realised in the domestic stock market being offset by the gain made in the foreign stock market.

The hedge ratio between UK and foreign stock indices is given as;

$$\beta_t^{12} = \frac{h_t^{12}}{h_t^2} \tag{3.10}$$

where β_t^{12} is the optimal hedge ratios of the portfolio. The optimal hedge ratio therefore seeks to minimise the variance of the position's value. As an improvement on existing literature, we estimate time-varying optimal portfolio weights and hedge ratios in order to capture the impact of changing market conditions (see Olson *et al.*, 2014).

In order to construct the portfolio of two risky assets (i.e. UK and foreign stock portfolio), we use the optimal weights in estimating the portfolio return and risk.

The rate of return on this bivariate portfolio is given as;

$$R_P = W_{1,t}R_{1,t} + W_{2,t}R_{2,t} \tag{3.11}$$

The variance of the bivariate portfolio is given as;

$$\sigma_{P,t}^2 = W_{1,t}^2\sigma_{1,t}^2 + W_{2,t}^2\sigma_{2,t}^2 + 2W_{1,t}W_{2,t}Cov(R_{1,t}, R_{2,t}) \tag{3.12}$$

where $Cov(R_{1,t}, R_{2,t}) = \rho_{12,t}\sigma_{1,t}\sigma_{2,t}$. The correlation values range from -1 to +1. The standard deviation of the bivariate portfolio measures the portfolio risk. We may find out if portfolio of

[57] These hedge ratios state the short position investor should take in foreign stock market to reduce the risk of a portfolio containing just domestic stock.

less than perfectly correlated assets offers better risk-return opportunities than highly correlated portfolio.

3.3.3 *Measurement of Value-at-Risk*

Value-at-Risk (VaR) can be described as a measure of potential loss with a given probability as a result of market movements during a certain holding period. Danielsson (2011) defines VaR as the minimum potential loss that a portfolio can incur in an adverse outcome. Also, Jorion (2007) defines VaR as the worst loss over a target horizon such that there is a low, pre-specified probability that the actual loss will be greater. VaR can be used to forecast the market risk or potential loss in the next trading period. Given these definitions, VaR can be described in a simple form as:

"With a probability of *F* percent, over the time period of *T*, the portfolio will not lose more than *S* dollars"

This suggests for example, that if a risk manager estimates the daily VaR at 1% confidence level as $100, then it is expected that there is a 99% chance that the next day loss of his portfolio's market value will not exceed $100. In other words, there is only a 1% chance that the portfolio will experience a loss of $100 or more.

VaR is measured using the parametric, semi-parametric and non-parametric approaches. In this analysis, the models considered include historical simulation, moving average, exponential weighted moving average (i.e. RiskMetrics) and generalised autoregressive conditional heteroscedasticity (GARCH).

A. Historical Simulation

Historical simulations (HS) is among the simplest methods which can be used to predict market risk. It assumes that there is repetition in history and therefore it is expected that the next period return will follow the same data generating process (DGP) as the past returns, that is, the DGP is time invariant. According to Burchi and Martelli (2016), the model assumes that the distribution of future returns is constant over time and corresponds to the observed distribution. One major strength of HS is that it directly captures nonlinear dependence in a manner that other methods may fail to account for. The sensitivity to outliers is pretty low and unlike parametric methods, this nonparametric method does not incorporate estimation error (Danielsson, 2011).

A fundamental flaw with this method is the assumption that the historical observations carry the same weight for forecasting risk and does not make any assumption about the form of the distribution. This could lead to inaccurate measurement in the presence of structural break in volatility. However, Alexander (2009) argues that HS method is gaining popularity because it does not assume financial returns distribution and dependencies of the risk factors are inferred directly from historical observations which imbibe the dynamic behaviour of risk factors in a natural and realistic manner.

B. Moving Average Model

Another less complicated risk forecasting model is the moving average (MA) model. The model is easy to compute and provide stable forecasts. The model uses the previous return to forecast the next period. It also assumes that observation are equally weighted which constitutes a fundamental problem when financial returns exhibit volatility clusters. It is significantly affected by change in estimation window length and could perhaps give an inaccurate risk forecast.

The MA forecasting model is given as;

$$\hat{\sigma}_t^2 = \frac{1}{W_E}\sum_{i=1}^{W_E} y_{t-i}^2 \tag{3.13}$$

where y_t is the observed return on day *t*; $\hat{\sigma}_t$ is the volatility forecast for day t and W_E is the length of the estimation window. Given a series of numbers and estimation window length, the first element of the MA is obtained by taking the average of the initial estimation window of the number series. The results obtained are however sensitive to the choice of estimation window length and may overestimate or underestimate risk.

C. RiskMetrics Model

The RiskMetrics model has the feature of allowing the conditional variance to be written as an exponentially weighted moving average (EWMA) of the past squared innovations and it is covariance non-stationary. The EWMA model shows that the current volatility forecast is a weighted average of previous volatility forecast and previous actual volatility. It can be calculated by weighting components with an exponential factor. EWMA can also be expressed as a normal integrated GARCH (*1,1*) model and is capable of eliminating the impact of large shocks in the economy by stating a decay factor. The returns are generated in the following recursive form;

$r_t = \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_t^2)$ (3.14)

The univariate EWMA conditional variance is given as;

$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1 - \boldsymbol{\lambda})\, \varepsilon_{t-1}^2$ (3.15)

where σ_{t-1}^2 and ε_{t-1}^2 are lagged conditional volatility and squared residuals; $\boldsymbol{\lambda} < 1$ refers to the decay factor or smoothing parameter. In line with Longerstaey (1996), we use a decay factor of $\boldsymbol{\lambda} = 0.94$, which he argues to produce on average a superior forecast of 1-day volatility.

The strength of the EWMA approach lie in the easiness of implementation unlike other parametric models. It is also useful in producing reasonable short-term volatility forecasts (Giot and Laurent, 2004). However, three weaknesses of EWMA have been identified. Firstly, the smoothing parameter is assumed to be constant for all assets and time periods. Secondly, empirical evidence shows that return distribution has a heavier tail than a normal distribution and as a result does not capture asymmetry effects. Thirdly, empirical evidence evinces that return series may exhibit long memory or long-term dependence on market volatility and the model is unable to provide long-horizon forecasts (Ding *et al.*, 1993; So, 2000; McMillan and Kambouroudis, 2009).

D. GARCH (*p*,*q*) model

The GARCH model uses optimal exponential weighting of historical returns to derive a volatility forecasts. The parameters of the model are estimated by maximum likelihood. Following the pitfalls of the RiskMetrics model, the GARCH model can better capture the inherent time-dependency within volatility. The conditional distribution of the GARCH model is assumed to follow normal distribution.

The conditional mean is given as;

$r_p = \mu + \varepsilon_t, \quad \mu_t|\Omega_{t-1} \sim N(0,1)$ (3.16)

The conditional variance is assumed to follow the GARCH (*1*,*1*) model;

$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \quad \varepsilon_t \sim N(0, H_t)$ (3.17)

where σ_t^2 is the current forecast variance; ε_{t-1}^2 is the lagged squared returns; σ_{t-1}^2 is the last period's forecast variance. The restriction that $\omega, \alpha, \beta > 0$ is placed on the model to ensure positive volatility forecasts, where α is the innovation coefficient and the decaying coefficient is given by β. The model is further restricted by $\alpha(1) + \beta(1) < 1$ to ensure covariance stationarity such that the effects of shocks do dies out. The size of $\alpha + \beta$ determines how fast the predictability of the process die out.

It is often the case that the return distribution is asymmetric or skewed which is in sharp contrast to what is implied by the normal GARCH model. Skewness and kurtosis have important implications for financial modelling, particularly for VaR. The Skewed Student density was proposed by Fernandez and Steel (1998) and has been extended to the GARCH framework by Lambert and Laurent (2000, 2001). In order to allow for the conditional distribution to be skewed, the log-likelihood function of the skewed *t*-GARCH model can be expressed as;

$$L_T = \ln\left[\Gamma\left(\frac{\nu+1}{2}\right)\right] - ln\left[\Gamma\left(\frac{\nu}{2}\right)\right] - 0.5ln[\Gamma((\nu-2)] + \ln\left[\Gamma\left(\frac{2}{\xi+\frac{1}{\xi}}\right)\right] + \ln(s) - 0.5\sum_{t=1}^{T}\left[ln\sigma_t^2 + (1+\nu)\ln\left(1+\frac{sz_t+m}{\nu-2}\,\xi^{-I_T}\right)\right]. \quad (3.18)$$

where ξ is the asymmetry parameter (i.e. $\xi > 0$ models the skewness), ν is the degree of freedom of the distribution; Γ (.) is the gamma function (see Lambert and Laurent (2001) for further details).

In summary, there are limitations trailing the methods despite the popularity of VaR. Just like any other methods, it is subject to model risk, the risk of errors arising from the use of inappropriate assumptions or wrong implementation of the model. In addition, Artzner *et al.* (1999) identify four axioms that must be satisfied for a risk measure to be described as *coherent*. They include monotonicity, subadditivity, positive homogeneity and translation invariance.[58] The subadditivity axiom which is important for portfolio diversification states that the risk to two different portfolios cannot be worse than the addition of the two individual risks. This implies that portfolio diversification should decrease portfolio risk. In other words, diversification effect could reduce the total portfolio risk based on the axiom of subadditivity. However, Danielsson (2011) argues that many assets including equities, exchange rates and commodities, do not have extremely fat tails and therefore may not violate the subadditivity axiom. Under returns that are normally distributed or linearly combined portfolio, subadditivity axiom is not violated given VaR is proportional to volatility.

[58] The monotonicity axiom state that if portfolio A never exceeds the values of portfolio B, the risk of B should never exceed the risk of A. The positive homogeneity axiom states that risk is directly proportional to the value of the portfolio as well. The translation invariance axiom states that an addition of a certain amount of capital reduces risk by the same amount (more details of these four properties are provided by Artzner *et al.* 1999; Frittelli and Gianin, 2002).

3.3.4 *Backtesting the Performance of VaR Models*

There are several ways to check the validation of the models which include backtesting, stress testing, scenario analysis and sensitivity analysis. In this analysis, we focus on backtesting, which is a popular procedure for evaluating the statistical precision and adequacy of the VaR forecast models over a given period. By checking the accuracy of the models, we will understand how well do the models capture possible losses on given confidence level and predict the size and frequency of possible losses. There are several backtesting methods which include unconditional coverage of Kupiec (1995), the conditional coverage of Christoffersen (1998), the density forecast evaluation approach of Berkowitz (2001), the duration-based approach of Christoffersen and Pelletier (2004) and the dynamic quantile of Engle and Manganelli (2004). We shall however focus on the Kupiec and Christoffersen coverage tests because they are widely employed backtesting procedures in investment risk management.

Generally, backtesting takes the ex-ante VaR forecasts from a particular model and compares them with ex-post realised returns. Simply, actual daily trading losses are compared with the estimated VaR. The number of days when the VaR estimate was inadequate to cover the actual trading losses are noted as number of 'exceptions or violations.' Under the Basel Accords, financial institutions that have excess number of violations will have to take immediate action to reduce their risk or improve the accuracy of VaR models.

The basic idea behind backtesting is to examine if the asset's 99th quantile VaR covers 99% of the actual returns. The actual returns that are not covered by the forecasted VaRs are referred to as violations. The essential tools used in backtesting are *violation ratios*. The number of violations and clustering can be tested using the unconditional and conditional coverage tests. A VaR limit violation occurs if the actual return on a particular day exceeds the VaR forecast. In other words, a violation occurs when the realized return exceed the estimated return. The violation ratio (VR) is calculated as;

$$\text{VR} = \frac{\text{Observed number of violations}}{\text{Expected number of violations}} = \frac{\nu_1}{\text{p x W}_\text{T}} \qquad (3.19)$$

A. Kupiec Unconditional Coverage Test

The unconditional coverage test proposed by Kupiec in 1995 follows a Bernoulli-distributed process with parameter *p*. The Bernoulli coverage test is nonparametric such that it does not assume a distribution for the returns and generally provides satisfactory benchmarks for the assessment of the accuracy of VaR models (Danielsson, 2011). A correct model would imply that the expected violation ratio is the tail area for each quantile. The test is used to ascertain the proportion of violations. To indicate whether a violation occurred on δ_t, values 1 and 0, represent a violation and no violation, respectively. The number of violations are collected in the variable ν, where ν_1 is the number of violations and ν_0 is the number of days without violations.

The likelihood ratio (LR) for the Bernoulli coverage test follows a distribution with one degree of freedom, and is defined in a framework where the data sample is split into a testing and estimation window. The likelihood ratio test for the unconditional coverage test is specified as;

$$LR_{UC} = 2\left(logL_R(p) - logL_U(\hat{p})\right) = 2\log\left[\frac{(1-\hat{p})^{\nu_0}(\hat{p})^{\nu_1}}{(1-p)^{\nu_0}(p)^{\nu_1}}\right] \sim \chi^2(1) \tag{3.20}$$

The testing window (W_T) is the data sample over which risk is forecast while the estimation window (W_E) is the number of observations used to forecast risk. Theoretically, VaR model under-forecasts risk if the violation ratio is greater than one and over-forecasts risk if the violation ratio is lesser than one. According to Gençay (2003), a violation ratio excessively greater than the expected ratio suggests that the model signals less capital allocation and the portfolio risk is not properly hedged.

The fundamental weakness of this test is that it neglects time variation in the violation sequence. That is to say, it cannot account for cluster of violations. It further fails to detect VaR measures that systematically under-estimate or over-estimate risk because of the effect of low power associated with the test (Danielsson, 2011).

B. Christoffersen Conditional Coverage Test

In order to account for cluster of violations over time (that is, violations happen one after the other) arising from volatility clustering, Christoffersen (1998) proposes the conditional coverage test. This backtesting procedure is capable of rejecting a model that generates either too many or too few clustered exceptions (autoregressive effect). The test requires accurate unconditional coverage and simultaneously ensures that the number of violations is independently, identically distributed through a test for independence. The procedure for the test is to calculate the probabilities of two consecutive violations (i.e. p_{11}) and the probability of a violation if there was no violation on the previous day (i.e. p_{01}).

The restricted likelihood function is given as;

$$L_R\left(\widehat{\Pi}_1\right) = (1-p_{01})^{\nu_{00}} p_{01}^{\nu_{00}} (1-p)^{\nu_{10}} p_{11}^{\nu_{11}} \tag{3.21}$$

The unrestricted likelihood function according to the null hypothesis of no clustering (that is, the violation of tomorrow does not depend on today seeing a violation) is given as;

$$L_U(\hat{\Pi}_0) = (1-\hat{p})^{\nu_{00}+\nu_{10}}\hat{p}^{\nu_{01}+\nu_{11}} \tag{3.22}$$

where ν_{ij} is the number of observations, and j follows i, and they are either *0 or 1*. For unrestricted likelihood function, $p_{01} = p_{11} = p$.

The likelihood ratio test for independence or conditional coverage is given as;

$$LR_{CC} = -2(\log L_U(\hat{\Pi}_0) - logL_R(\hat{\Pi}_1)) \sim \chi^2(1) \tag{3.23}$$

To forecast the VaR sequence, a method of fixed-window rolling sample is adopted. A key advantage of this model is that it allows to test both unconditional coverage and independence properties. Also, the method is easy to implement and can recognize the source of failure. A major weakness with backtesting is that it relies on asymptotic distributions. According to Danielsson (2011), this test will have no power to discover departures from independence if the likelihood of VaR being violated today depends on whether VaR was violated 2 days ago, rather than violations on yesterday's VaR. As a consequence, the independence property will not be fulfilled.

3.4 Dataset

3.4.1 *Data Description*

We employ the daily observations for a large cohort of stock returns for developed, emerging and frontier markets over the period 6th March 1999 to 5th March 2015. The data period used is the same for all individual markets except for MSCI Frontier market index that started trading from 31st May 2002. There are 9 markets selected from developed countries (2 from North America, 4 from Western Europe and 3 from Pacific), 9 from emerging countries (2 from Eastern Europe, 2 from Latin America, 3 from Asia and 2 from Africa), 8 from frontier countries (2 from Eastern Europe, 2 from South/Central America, 2 from Sub-Saharan Africa and 2 from South Asia) and 4 MSCI specialised markets.[59] These stock indices invariably contain stocks with the highest market capitalisation and liquidity in their respective countries.

The selection of national stock indices follows the MSCI market classification into developed, emerging and frontier markets based on the criteria of economic development, market size and liquidity as well as market accessibility and investment restrictions. However, the inclusion of immature markets is important in understanding the international stock dynamics from the viewpoint of a mature market. Overall, our selection of countries accommodates principal markets along regional representation which will help to comprehend the changing nature of information transmission across the globe. In addition, the daily series improve the power of the test of cross-border linkages, hence enabling portfolio managers and investors to effectively construct and manage their asset portfolios.

This study further considers the implications on asset price behaviours and dynamic financial linkages due to rapidly changing economic conditions, hence splitting the sample period with a total observations of 4170 for each market into two equal sub-periods. The first period, called the 'Great Moderation (GM)' is characterised with less significant economic events, macroeconomic stability and moderate volatility. Although, this period has been argued by many researchers to have started in the mid-1980s but in this study, we consider the period from

[59] The 9 developed markets include FTSE (UK); DAX 30 (Germany- GER); CAC 40 (France - FRA); FTSE MIB 40 (Italy - ITA); S&P 500 (US); S&P/TSX (Canada - CAN); NIKKEI 225 (Japan - JAP); HANG SENG (Hong Kong - HK); S&P/ASX 200 (Australia - AUS). The 9 emerging markets include RTS (Russia - RUS); WIG (Poland - POL); IPC (Mexico - MEX); BVSP (Brazil - BRZ); CNX Nifty (India - IND); SSE Composite index (China - CHI); BIST 100 (Turkey - TUR); EGX (Egypt - EGY); FTSE/JSE (South Africa - SA). The 8 frontier markets include BET (Romania - ROM); PFTS (Ukraine - UKR); MERVAL (Argentina - ARG); JMI (Jamaica - JAM); NSE All share index (Nigeria - NIG); NSE 20 (Kenya - KEN); KSE 100 (Pakistan - PAK); CSE (Sri Lanka - SRL). The 4 specialised markets include MSCI World (Developed markets - DEV); and Euro Stoxx 50 (Euro Area - EURO); MSCI Emerging markets (EM); MSCI Frontier markets (FM).

6th March 1999 until the start of the global financial crisis on 5th March 2007.[60] The second period, called the 'Great Austerity (GA),' is characterised with many significant economic events, macroeconomic instability and excessive volatility, starting from 6th March 2007 till the end of the data series (i.e. 5th March 2015).[61] The rationale for analysing these two typical periods is to determine the effects of distinct economic environments on volatility transmission, correlation dynamics, portfolio design, hedging strategies, as well as downside risk.

The samples were selected given the increasing integration of international financial markets since the introduction of euro currency. All prices used in this analysis are denominated in local currency for the purpose of understanding directly the integration of these markets without considering the effect of exchange rate risk.[62] In addition, we use the local currency on the assumption that most stock market activity are dominated by domestic buyers and sellers (see Hon *et al.*, 2007).

Table 3.1 shows the salient characteristics of the stock markets under scrutiny. The UK economy is the fifth largest national economy measured by nominal GDP with a share of world GDP of 3.2%. In the last two decades, the world's equity markets have experience an unprecedented growth of 172% from £24.5 trillion in 1995 to $66.5 trillion in 2014. In the same period, the UK stock market capitalisation has grown by 139% from $1.32 trillion to $3.18 trillion. The ratio of stock market capitalisation to GDP is commonly used as a proxy for stock market development.[63] The UK stock market capitalisation to GDP is approximately 115% by current data, which suggests that the UK stock market is large in comparison with its national economy. Apart from UK's overvalued financial markets, the markets in US, Canada, Hong Kong, South Africa are overvalued as well. Some studies have found that countries with higher market capitalisation to GDP are on average better integrated with world financial markets (see

[60] We use the cut-off date of 5th March 2007 because it coincides with HSBC's announcement of one portfolio of purchased sub-prime mortgages evidencing much higher delinquency than had been built into the pricing of these products (see, BoE Financial Stability Report, 2009). The 'Great Moderation' from 6th March 1999 to 5th March 2007 was characterised with low business cycles fluctuations unlike the 'Great Austerity'. It is a period of unprecedented macroeconomic stability

[61] The 'Great Austerity' from 6th March 2007 to 5th March 2015 was characterised with high macroeconomic fundamental volatility, Great Recession and debt crisis.

[62] Heston and Rouwenhorst (1994) conclude that foreign exchange rates have no material impact on the results even when we employ notional values. Panapoulou and Pantelidis (2009) argue that employing local currency returns is similar to holding a portfolio where foreign exchange risk has been absolutely removed. Some other studies on international diversification have ignored currency effects (see You and Daigler, 2010).

[63] The stock market capitalisation-to-GDP ratio is used as an indicator of stock market size in terms of undervaluation or overvaluation of the overall market

Bekaert and Harvey, 1995; Ng, 2000; Baele 2005). Also, the stock turnover ratio of the UK market portrays that it is one of the most liquid markets in the world.[64]

The capital city of UK, London is at top in Global Financial Centre Index even though the UK market constitutes approximately 5.4% of the global equity markets. The top ranking ahead of US justifies that UK financial system has performed exceptionally well based on the five key criteria; "business environment," "financial sector development," "infrastructure factors," "human capital," and "reputation and general factors" (Global Finance Centre Index, 2016).

Apart from Hong Kong, Canada and Australia, the UK has the highest number of listed companies per million people. Similarly, the UK is second to Hong Kong in gross portfolio equity assets to GDP.[65] The equity market of Hong Kong of 189% is large compare to its economy as shown by the ratio of gross portfolio equity assets to GDP ratio. The characteristics of the frontier markets portray weak financial market development given the low market turnover ratio, small market-capitalisation to GDP and few listed companies due to investment restrictions, liquidity constraints and capital controls.

In summary, though substantial literature has focused on US market relationship with the rest of the world, we justify the selection of UK market to demonstrate the potential benefits of diversification and risk management as a leading financial centre of the world. Indeed, UK has a developed financial infrastructure and understanding the financial linkage between UK and other foreign markets will have important implications for financial market operators and policymakers.

[64] The stock turnover ratio measures the value of stock transactions relative to the size of the market (i.e. market capitalisation) and is commonly used as proxy for market liquidity.
[65] The gross portfolio equity assets to GDP ratio is used as an indicator of total ownership of equity and may be used as a proxy for financial development.

Table 3.1: Features of the Stock Markets under Scrutiny

Countries/ Markets	**Stock Market Indices**	**Gross portfolio equity assets to GDP (2012)**	**Number of Listed Companies per Million People (2012)**	**Market cap. % of GDP 2012**	**Stocks traded, turnover ratio (%) (2012)**	**GDP, PPP (Current International US$tn) (2013)**
UK	FTSE 100	57.77	34.21	115.5	96.05	2.450
Germany	DAX 30	25.28	8.27	42.06	91.77	3.540
France	CAC 40	24.43	13.13	67.99	66.43	2.480
Italy	FTSE MIB 40	29.13	4.69	23.15	54.63	2.110
US	S&P 500	29.98	13.07	115.5	84.04	16.80
Canada	S&P/TSX	15.67	111.53	110.0	61.58	1.510
Japan	NIKKEI 225	14.49	27.20	61.82	99.85	4.610
Hong Kong	HANG SENG	189.4	203.92	421.9	123.1	0.380
Australia	S&P/ASX 200	22.85	86.19	83.84	84.65	0.990
Developed markets	MSCI Developed	42.21	55.80	115.8	84.68	3.870
Euro Area	EURO STOXX 50	17.82	13.13	36.53	40.13	13.41
Russia	RTS	0.306	1.930	43.48	87.64	3.590
Poland	WIG	2.178	21.90	35.18	42.56	0.910
Mexico	IPC	N/A	1.080	44.25	99.85	2.000
Brazil	BVSP	0.753	1.780	54.69	67.88	3.210
India	CNX NIFTY 50	0.092	4.180	68.97	54.63	6.780
China	SSE	1.616	1.850	44.92	164.4	16.60
Turkey	BIST 100	0.027	5.470	39.14	135.5	1.410
Egypt	EGX 30	0.268	2.890	22.07	37.79	0.910
South Afr.	FTSE/JSE	44.17	6.650	154.1	78.46	0.680

Emerging markets	MSCI Emerging	5.490	5.303	56.31	85.41	4.010
Argentina	MERV	0.017	2.460	6.470	3.750	0.310
Jamaica	JMI	0.428	13.29	43.19	3.020	0.020
Romania	BET	0.630	3.840	9.400	11.45	0.380
Ukraine	PFTS	0.045	4.340	11.78	5.210	0.390
Kenya	NSE 20	N/A	1.320	29.34	8.070	0.120
Nigeria	NSE ASI	3.250	1.140	12.23	8.780	0.970
Pakistan	KSE	0.091	3.190	19.44	31.30	0.840
Sri Lanka	CSE	4.382	14.12	28.70	9.180	0.190
Frontier markets	MSCI Frontier	1.263	5.463	20.07	10.09	0.403

Source: World Development Indicators and Federal Reserve Bank of St. Louis.

Notes: Apart from Japanese, Euro Area, Argentine and Kenyan stock indices that are price-weighted index, all other markets are Capitalisation-weighted index. The values for the MSCI developed, emerging and frontier markets are estimated by averaging the values of their respective indices. N/A indicates that data is not available

3.4.2 *Preliminary Statistics*

We report the descriptive statistics of the daily stock returns (that is, logged first differences) of the understudy markets for both the GM and GA periods. Figure 3.2 shows the closing prices of selected stock markets and they demonstrate that the stock price indices are characterised by high fluctuations, especially in crisis periods. Indeed, the UK stock market shares familiar phases of market dynamics with the foreign stock markets. In addition, the GA period shows more swings in market movements than the GM period. The stock indices behave alike such that prices trend upward in the GM period while they trend downward from 2007 due to the outbreak of global economic and financial crisis. However, the financial markets have rebounded from mid-2009 after the introduction of fiscal stimulus and monetary easing by several countries to stabilise their economies.

The descriptive statistics for the stock markets are set out in Table 3.2. All the stock returns are stationary on first differencing based on unit root tests (results for stationarity test are not reported). During the GM period, the *t*-test results indicate that the mean returns are statistically different from zero for most markets with the Ukrainian market having the highest stock returns of 0.17%. The UK stock market yields the lowest returns and in fact, the only country with negative mean returns in the GM period. Additionally, the unconditional volatility (as measured by standard deviations) is highest in Turkish market and lowest in MSCI frontier/Australian markets in the same period. In the GA period, the *t*-test results show that the mean returns are not statistically different from zero for most markets with the Argentine market having the highest stock returns of 0.07%. In the same period, the Italian stock market yields the highest negative returns. The highest volatility is the Russian market while the lowest volatility is the MSCI frontier markets along the same lines.

Furthermore, the results indicate more negative returns, higher standard deviations, increased kurtosis and higher negative skewness during the GA period than the GM. Similarly, all foreign markets provide higher returns than UK market in the GM period whereas 20 out of 29 foreign markets provide higher returns than the UK market in the GA period. Also, 19/17 out of 29 foreign markets indicate much higher risk than the UK market in the GM/GA periods. Further comparison between the two subsamples suggests that the GA period is more turbulent with increased volatility in most markets. The results for the specialised markets indicate that the MSCI frontier markets have the highest returns and lowest risk in the GM period while the MSCI developed markets have the highest returns and a lower risk after MSCI frontier markets in the GA period. As a result of lower volatility in most frontier stock markets, they may be a good hedge instrument for UK stock portfolio.

In a similar fashion, Figure 3.3 shows the graphical representation of risk-return profile of the markets during the GM and GA periods. The risk-return profile of the markets is widely divergent in the GM period while it clusters in the GA period. This suggests that increase integration or convergence is not a rare phenomenon in crisis periods. With the exception of Ukraine, Romania and Argentina, the frontier markets show considerably lower risk level than the emerging and developed markets in both GM and GA periods. However, the risk-return profile of most frontier markets is less attractive in the GA period because of high negative returns. Due to the prevalence of crisis in GA period, the level of returns becomes negative in 9 out of 30 markets. The risk-return profile of Turkey and Russia is the worst performing in GM and GA periods, respectively. The UK and US, in particular show higher returns but at the cost of increased volatility in the GA period. We allude the changes in their risk-return profile, perhaps to the quantitative easing policies implemented to combat the 2008 stock market crash. As a result of the different level of risk-return performance, there are possibilities of exploiting these opportunities from the standpoint of portfolio diversification.

Additionally, all markets exhibit negative skewness in the GA period and most markets in GM period suggesting the prevalence of negative shocks. According to Post, Van Vliet and Levy (2008), the skewness of the distribution of financial asset returns is generally caused by information asymmetry and investors' preference. The high kurtosis values for all the series indicate fat-tailed distribution, presence of extreme observations and volatility clustering. The Jarque-Bera joint tests for the null of normality provide further evidence that the daily returns are not normally distributed in all the markets. The preliminary analysis suggests the use of a GARCH-type process to account for fat-tail, information asymmetry, persistence, clustering and time-varying volatility.

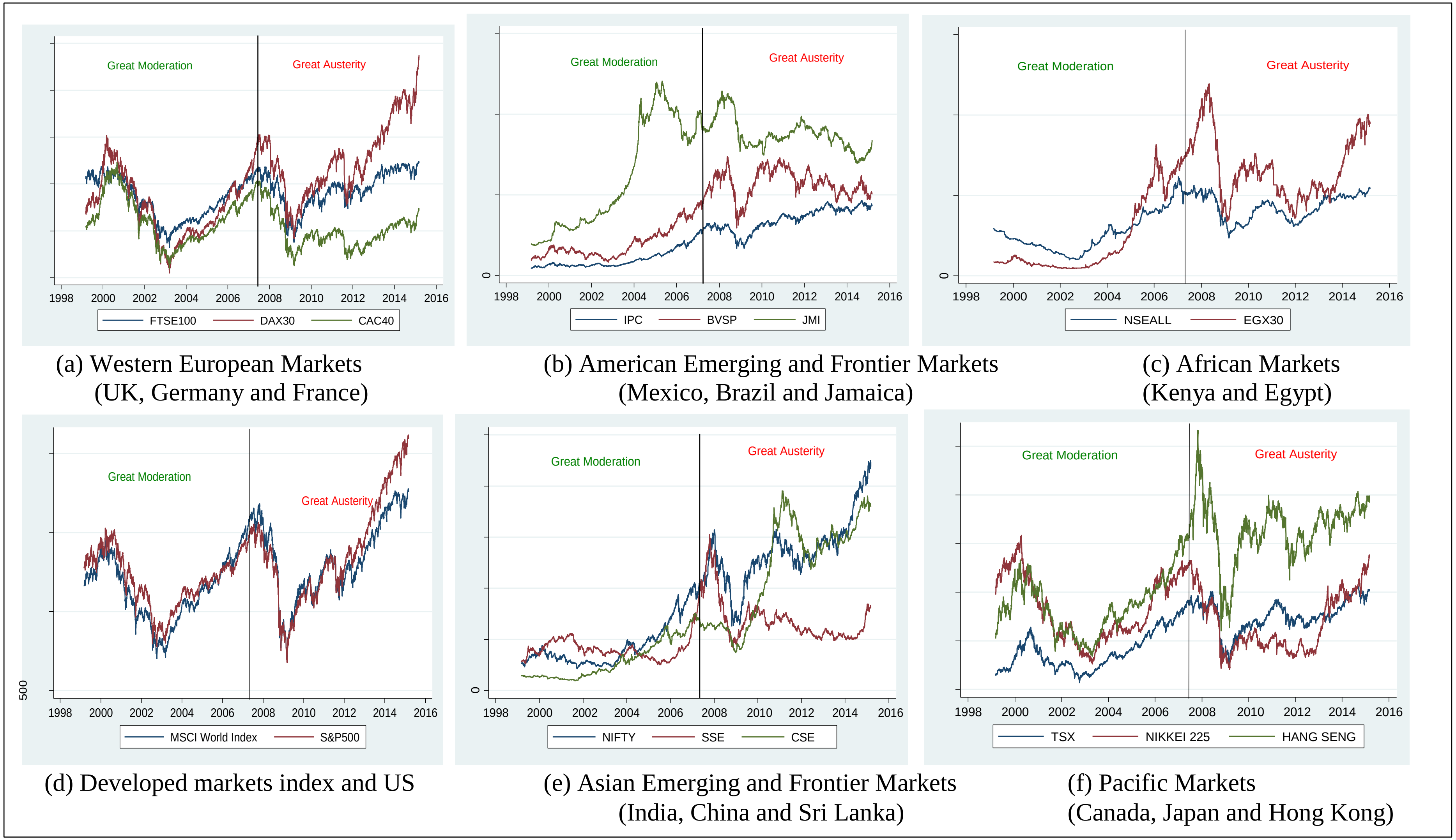
We carry out tests for equality of means, standard deviations and distributions between the GM and GA periods. For the equality of two means, the two-sample *t*-test soundly rejects the null hypothesis that the returns are the same in Russia, Jamaica, Romania, Ukraine, Nigeria and MSCI frontier markets. This suggests that the mean values between GM and GA periods are equal for most markets. For the equality of two variances, the Levine test rejects the null hypothesis that the standard deviation are the same in all markets, suggesting that volatility are not the same in both periods. For the equality of distributions, the Kolmogorov-Smirnov test rejects the hypothesis that the distributions are the same in 20 out of 30 markets.

In summary, the preliminary evidence is already leaning toward the necessity to investigate comprehensively portfolio management that includes UK and other foreign stock markets. In the next session, we shall use multivariate volatility and value-at-risk models to investigate volatility transmission, correlation dynamics, portfolio allocation, hedging strategies and tail risk between UK and a large cohort of foreign stock markets.

Table 3.2: Descriptive Statistics

Markets	**Great Moderation (Obs. = 2086)**					**Great Austerity (Obs. = 2086)**					**Equality of mean**	**Equality of variance**	**Equality of distributions**
	Mean ($*10^{-3}$)	**S.D.**	**Skw**	**Kur**	**Jarque Bera**	**Mean ($*10^{-3}$)**	**S.D.**	**Skw**	**Kur**	**Jarque Bera**	**Two sample t-test**	**Levine test**	**Kolmogorov-Smirnov test**
UK	-0.006	0.011	-0.219**	6.249**	180.4**	0.061	0.013	-0.123*	10.72**	326.3**	-0.068 (-0.180)	0.012 (0.735**)	0.028
Germany	0.144	0.016	-0.090	6.024**	156.1**	0.266	0.015	0.066	9.369**	283.7**	-0.122 (-0.226)	0.015 (1.107*)	0.035
France	0.120	0.014	-0.092*	6.128**	161.1**	-0.044	0.016	0.078	8.914**	269.9**	0.164 (0.364)	0.015 (0.785**)	0.023
Italy	0.031	0.012	-0.194**	6.658**	195.4**	-0.286	0.017	-0.024	6.829**	190.1**	0.317 (0.695)	0.015 (0.496**)	0.084**
US	0.036	0.011	0.084	5.658**	137.5**	0.203	0.014	-0.316**	12.73**	402.2**	-0.167 (-0.446)	0.012 (0.632**)	0.045*
Canada	0.328	0.010	-0.578**	8.517**	355.9**	0.082	0.013	-0.688**	13.19**	515.8**	0.246 (0.723)	0.011 (0.624**)	0.034
Japan	0.053	0.013	-0.144**	4.879**	100.3**	0.056	0.016	-0.565**	11.40**	435.7**	-0.003 (-0.006)	0.015 (0.681**)	0.023
Hong Kong	0.288	0.013	-0.295**	6.751**	215.7**	0.129	0.017	0.072	11.89**	351.5**	0.158 (0.336)	0.015 (0.605**)	0.035
Australia	0.339*	0.007	-0.573**	6.791**	288.4**	0.021	0.012	-0.398**	7.690**	276.3**	0.319 (1.056)	0.010 (0.366**)	0.089**
Developed	0.106	0.009	-0.034**	5.427**	123.4**	0.094	0.012	-0.434**	11.00**	388.6**	0.012 (0.039)	0.010 (0.531**)	0.039*
Euro Area	0.057	0.014	-0.056**	6.047**	155.4**	-0.050	0.016	0.041**	8.437**	252.4**	0.107 (0.235)	0.015 (0.836**)	0.028
Russia	1.522**	0.023	-0.315**	8.167**	275.4**	-0.321	0.023	-0.346**	14.85**	450.5**	1.843 (2.605**)	0.023 (0.960**)	0.062**
Poland	0.641*	0.013	-0.193**	5.515**	140.4**	0.023	0.013	-0.454**	7.097**	267.2**	0.619 (1.539)	0.014 (1.163**)	0.035
Mexico	0.856**	0.014	-0.011	5.737**	139.1**	0.248	0.013	0.170**	10.06**	312.7**	0.608 (1.448)	0.018 (0.972**)	0.067**
Brazil	0.705	0.018	-0.166**	4.279**	67.88**	0.098	0.018	0.021	9.619**	289.9**	0.607 (1.105)	0.013 (0.737**)	0.063**
India	0.586	0.015	-0.570**	8.446**	351.3**	0.439	0.016	0.093*	13.58**	389.6**	0.146 (0.307)	0.015 (0.962**)	0.062**
China	0.432	0.014	0.388**	8.765**	312.1**	0.078	0.017	-0.364**	6.973**	239.6**	0.353 (0.734)	0.015 (0.962**)	0.048**
Turkey	1.118	0.027	0.106*	8.560**	259.9**	0.348	0.017	-0.225**	7.263**	225.3**	0.770 (1.101)	0.023 (2.459**)	0.101**
Egypt	1.009**	0.019	0.470**	11.59**	412.9**	0.149	0.017	-1.229**	12.99**	710.3**	0.860 (1.637)	0.017 (0.982**)	0.039*
South Africa	0.696**	0.011	-0.238**	6.452**	192.5**	0.361	0.013	-0.122*	6.998**	202.3**	0.335 (0.916)	0.012 (0.785**)	0.032
Emerging	0.489*	0.010	-0.596**	5.213**	218.7**	0.069	0.014	-0.419**	11.19**	389.8**	0.419 (1.135)	0.012 (0.506**)	0.049**
Argentina	0.773	0.022	0.195**	7.971**	248.3**	0.769	0.020	-0.618**	7.725**	340.2**	0.004 (0.007)	0.021 (1.140**)	0.038*
Jamaica	0.739**	0.008	0.931**	14.94**	635.9**	-0.049	0.007	0.159**	18.95**	483.9**	0.789 (3.416**)	0.008 (1.201**)	0.079**
Romania	1.446**	0.017	0.099	24.76**	545.8**	-0.055	0.017	-0.606**	11.73**	456.2**	1.501 (2.878**)	0.017 (1.059**)	0.047**
Ukraine	1.704**	0.018	0.386**	19.14**	526.6**	-0.169	0.019	-0.071	12.30**	361.1**	1.874 (3.295**)	0.018 (0.888**)	0.073**
Kenya	0.278	0.009	0.088	52.41**	714.7**	0.015	0.009	0.568**	12.65**	465.5**	0.263 (0.919)	0.009 (1.182**)	0.069**
Nigeria	0.968**	0.009	-0.031	9.714**	292.9**	-0.134	0.010	-0.089*	5.633**	136.6**	1.112 (3.613**)	0.010 (0.760**)	0.099**
Pakistan	1.153**	0.016	-0.265**	6.072**	179.3**	0.535*	0.012	-0.353**	7.308**	250.9**	0.618 (1.422)	0.014 (1.855**)	0.105**
Sri Lanka	0.768**	0.013	0.089	37.92**	645.0**	0.425*	0.009	0.245**	8.896**	287.6**	0.343 (0.964)	0.011 (2.088**)	0.043**
Frontier	0.888**	0.007	-0.194	10.05**	191.8**	-0.128	0.005	-1.949**	21.13**	1106**	0.739 (2.825**)	0.008 (0.577**)	0.062

Notes: The superscripts '**'and '*' denotes significant levels at 5% and 10%, respectively.



(a) Western European Markets
(UK, Germany and France)

(b) American Emerging and Frontier Markets
(Mexico, Brazil and Jamaica)

(c) African Markets
(Kenya and Egypt)

(d) Developed markets index and US

(e) Asian Emerging and Frontier Markets
(India, China and Sri Lanka)

(f) Pacific Markets
(Canada, Japan and Hong Kong)

Figure 3.2: Closing Stock Prices for Selected Markets

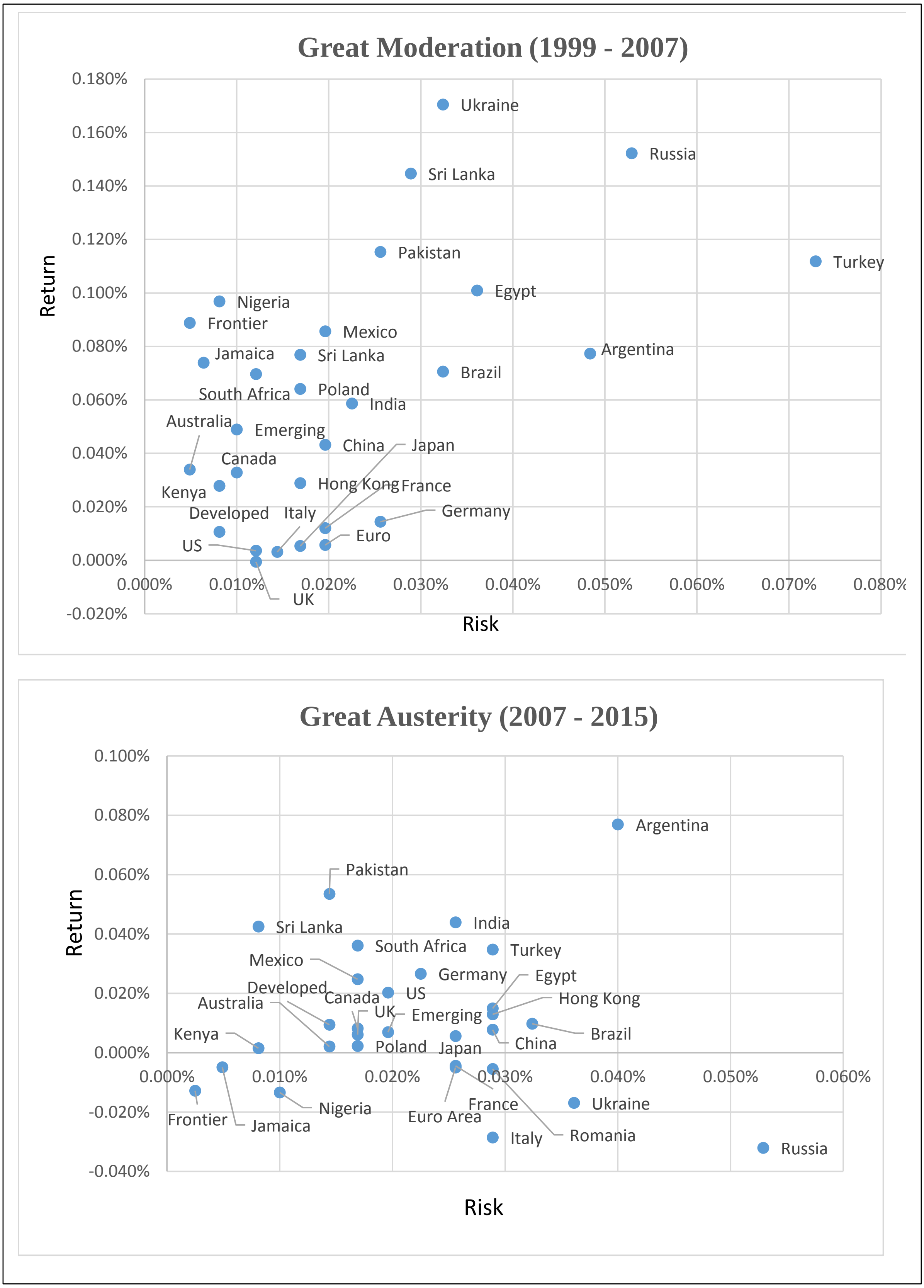


Figure 3.3: Risk-Return Profile of Market Indices

3.5 Empirical Results and Discussions

This whole section sets out the empirical results. Section 3.5.1 presents the empirical evidence on spillover effects for the GM and GA periods. We report the findings of portfolio return, portfolio risk and time-varying conditional correlation in section 3.5.2. Section 3.5.3 discusses the results for dynamic optimal portfolio weights and risk minimising hedge ratios. Finally, the analysis of value-at-risk and backtesting procedures are reported in section 3.5.4.

3.5.1 Information Spillover Effects

The empirical estimates of the ASY BEKK under the student *t*-distribution are reported in Table 3.3 and Table 3.4. We use the *delta method* to evaluate the statistical significance of the coefficients of the transmission effects since the elementary parameters consist of non-linear function. All the diagonal parameters for the ARCH and GARCH effects are statistically significant, suggesting that own domestic past shocks and volatilities affect the conditional variances of all the markets under consideration in both the GM and GA periods. This further justifies the appropriateness of the BEKK GARCH (*1,1*) specifications. The off-diagonal elements of matrix *A* and *B* measure the cross-market effects such that shock and volatility spill over between UK and foreign stock markets. The values for the own-market volatilities suggest high degree of volatility persistence in the stock returns. It is evident that the values of estimated β_{11}/β_{22} coefficients are higher than the estimated α_{11}/α_{22} coefficients, which suggests that the long-run persistence in current stock volatility is greater than its short-run persistence. This further indicates that the estimated conditional stock volatility tends to adapt more quickly to significant impact of past volatility than the past shocks. This will assist investors and portfolio managers to execute active portfolio management based on long-run persistence and contemporaneous information shocks.

The stationarity condition for the BEKK covariance matrix H_t is satisfied as eigenvalues are closer to unity suggesting high level of persistent shocks. The likelihood ratio test soundly rejects the null of constant covariance on the off-diagonal element of matrix H_t in all markets except for Argentina, Jamaican, Kenyan, Nigerian and MSCI frontier markets during the GM period and German, Italian and MSCI frontier markets during the GA period.[66] Likewise, the likelihood ratio test of the null of no asymmetry effect, which is a joint test of $\delta_{11} = \delta_{12} = \delta_{21} = \delta_{22}$, is easily rejected in all the markets.

[66] The LR statistic tests for the null (H_0: $\alpha_{12} = \alpha_{21} = \beta_{21} = \beta_{21} = \delta_{12} = \delta_{21} = 0$).

In the GM period, we find significant bidirectional volatility spillovers between UK and Italy. This suggests that the impact of past volatility originating from the Italian market decreases the UK current volatility ($h_{t-1,12}$ = -0.025), as does a past volatility originating from UK have upon the Italian market's current volatility ($h_{t-1,21}$= -0.033). Similarly, the impact of past volatility originating from UK market decreases current volatility in Germany/France/Euro Area\Ukraine, while it increases current volatility in Sri Lanka market. Conversely, unidirectional past volatility spills over from Australia/Russia/South Africa/MSCI emerging and diminishes current volatility of UK. In addition, unidirectional past volatility spills over from US/Canada and reduces current volatility of UK market. This suggests that past volatility originating from North American unilaterally causes current volatility to rise in the UK market, suggesting a form of market contagion. A sharp twist in bidirectional relationship, we find that impact of past volatility originating from the Mexico/India markets decreases UK current volatility while the past volatility originating from UK market increases current volatility of Mexico/India.

Furthermore, we find significant bidirectional shock spillovers between UK and France. This suggests that the impact of past shock originating from the French market increases the UK current volatility ($\varepsilon_{t-1,1}\varepsilon_{t-1,2}$ = 0.013), as does a past shock originating from UK have upon the Italian market's current volatility ($\varepsilon_{t-1,2}\varepsilon_{t-1,1}$ = 0.035). Similarly, the impact of past shock originating from UK market increases current volatility in Italy/Canada/MSCI developed/Euro Area, while it decreases current volatility in Sri Lanka. Conversely, the impact of past shocks from Hong Kong/Russia/MSCI frontier markets increases current volatility in UK market, whereas unidirectional past shock spilover from US/Kenya diminishes current volatility of UK market. In addition to evidence of bidirectional shock spillovers, we find that impact of past shocks originating from the Brazilian (Indian) market decreases (increases) UK current volatility while the UK past shock increases (decreases) the current volatility of the Brazilian (Indian) market.

Turning to the asymmetric effects, we find bidirectional relationship that the current volatility of UK market increases more in response to the bad news about Germany/France/Italy/Euro Area and vice-versa. Similarly, we show that UK current volatility increases more in response to the bad news about Poland/India whereas current volatility increases in US/Hong Kong/MSCI developed/Ukraine markets in response to bad news about UK market. The overall result supports that bad news originating from UK market have more dominant impact on other foreign markets. This corroborates with existing findings that negative news have bigger impact on subsequent volatility than positive news (see Conrad *et al.,* 1991; Glosten *et al.,* 1993; Kroner and Ng, 1998; Michayluk *et al.,* 2006; Li., 2007).

In the GA period, we find significant bidirectional volatility spillovers between UK and Italy/US/Australia/MSCI developed/Euro Area/Mexico/India/MSCI emerging/Kenya. For instance, the impact of past volatility originating from the US market increases UK current volatility ($h_{t-1,12}$ = 0.358), as does a past volatility originating from UK has on decreasing the US current volatility ($h_{t-1,21}$ = -0.339). The linkage between these two markets is the strongest among all developed markets, suggesting a significant level of stock market integration. Furthermore, the impact of past volatility originating from the UK market increases current volatility in the Japanese/Jamaican market while, it decreases current volatility in France/Russia/Poland/China/Argentina/Romania/MSCI frontier. Overall, the UK market is highly exposed to volatility transmission emanating from major markets in Europe, America, Asia and expectedly in minor markets in Africa. The reason may be due to the highly sensitive and volatile nature of these minor markets arising from political and macroeconomic instability thereby transmitting volatility to major markets.

Similarly, we find bidirectional shock spillovers between UK and Italy/Australia/MSCI developed/Euro Area/Russia/Mexico/India/Kenya/Nigeria. For instance, the impact of past shocks originating from Italian market decreases current volatility in the UK market ($\varepsilon_{t-1,1}\varepsilon_{t-1,2}$ = -0.029), while the past shock originating from the UK market increases current volatility in the Italian market ($\varepsilon_{t-1,2}\varepsilon_{t-1,1}$ = 0.044). However, the evidence of unidirectional volatility spillover indicates that previous shock originating from South Africa increases current volatility in UK, whereas previous shock originating from UK increases current volatility in France/Poland/Turkey/Egypt/Argentina/Romania/Ukraine/MSCI frontier. This suggests a form of market contagion between UK and these foreign markets. In contrast, past shock originating from US/MSCI emerging reduces current volatility in UK market. Finally on asymmetric effects, we find that UK market volatility increases in response to bad news originating from Canada/India/South Africa, whereas bad news emanating from UK market increase current volatility in Egypt/Argentina/Ukraine/Kenya. There is a diminished role for information asymmetries in the GA period.

We carry out diagnostic checks based on tests for serial correlation and heteroskedascitiy on the residuals of the bivariate ASY BEKK model. This model generate reasonable conditional variance and covariance estimates suggesting that our multivariate GARCH specification is robust. Overall, the results suggest that the empirical estimates obtained are less affected by serial correlation and heteroscedasticity.

We summarise the significant spillover effects during GM and GA periods in Table 3.5 based on the point estimates of the BEKK GARCH model. We find stronger financial linkages in the GA period. These findings corroborate with existing evidence that volatility spillovers are more pronounced during the market crisis (see Hamao *et al.,* 1990; Kim *et al*; 2005; Baele, 2005; Caporale *et al.,* 2006). However, these studies were performed prior to 2003 with limited cross-markets analysis and therefore does not provide evidence of the nature of interdependence between the UK and other foreign markets in more recent years. The linkage between UK and Italy is the strongest in the developed markets, while the weakest linkage is between UK and Japan/Hong Kong. In the emerging markets, the strongest linkage is between UK and India, whereas the weakest linkage is between UK and China/Turkey. In the frontier markets, the strongest linkage is between UK and Kenya while the weakest linkage is between UK and Pakistan. During both periods, there is neither shock nor volatility spillovers between UK and Pakistan. Overall, the linkage between UK and developed markets is far stronger than with emerging or frontier market countries.

We conclude that the degree of financial openness will determine the magnitude of the transmission of shocks and volatilities across markets. Therefore, markets with lower degree of openness and barriers to capital flows will have weak financial linkages, while markets with higher degree of openness and absence of barriers to capital flows will have strong financial linkages. However, such barriers tend to drop in the GA period. These results have important implications on tackling problems of portfolio choice, hedging and downside risk. We shall discuss the evidence on tackling these issues in subsequent sessions.

Table 3.3: Great Moderation - Asymmetric BEKK (*1*,*1*)

$$h_{11,t} = c_{11} + \left(\alpha_{11}^2\varepsilon_{11,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1}\right) + \left(\delta_{11}^2\eta_{11,t-1}^2 + 2\delta_{11}\delta_{21}\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}^2\eta_{22,t-1}^2\right)$$

$$h_{22,t} = c_{22} + \left(\alpha_{12}^2\varepsilon_{11,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{22}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1}\right) + \left(\delta_{12}^2\eta_{11,t-1}^2 + 2\delta_{12}\delta_{22}\eta_{11,t-1}\eta_{22,t-1} + \delta_{22}^2\eta_{22,t-1}^2\right)$$

	$h_{11,t-1}$	$h_{22,t-1}$	$h_{12,t-1}$	$\varepsilon_{11,t-1}^2$	$\varepsilon_{22,t-1}^2$	$\varepsilon_{11,t-1}\varepsilon_{22,t-1}$	$\eta_{11,t-1}^2$	$\eta_{22,t-1}^2$	$\eta_{11,t-1}\eta_{22,t-1}$	Q(12)	Q^2(12)
Panel A: Developed Markets											
UK	0.917**	5x10^{-5}	-0.013	0.062**	0.001	0.016	0.046*	0.025**	-0.067**	11.71	6.959
	(0.019)	(8x10^{-5})	(0.011)	(0.021)	(0.002)	(0.012)	(0.025)	(0.012)	(0.033)		
GER	0.000	0.946**	-0.040*	0.003	0.046**	0.024	0.118**	0.035*	-0.129**	5.891	0.860
	(0.000)	(0.014)	(0.023)	(0.006)	(0.015)	(0.018)	(0.043)	(0.018)	(0.056)		
UK	0.914**	2x10^{-5}	-0.009	0.062**	0.001**	0.013**	0.088**	0.058**	-0.143**	11.21	8.274
	(0.009)	(3x10^{-5})	(0.007)	(0.006)	(0.000)	(0.003)	(0.031)	(0.021)	(0.048)		
FRA	0.001	0.962**	-0.063**	0.009**	0.032**	0.035**	0.146**	0.070**	-0.203**	12.76	8.349
	(0.000)	(0.008)	(0.006)	(0.003)	(0.003)	(0.003)	(0.046)	(0.028)	(0.069)		
UK	0.934**	1x10^{-3}	-0.025**	0.059**	0.001	0.014	0.056**	0.034*	-0.087*	11.41	9.200
	(0.013)	(8x10^{-4})	(0.007)	(0.016)	(0.016)	(0.014)	(0.027)	(0.021)	(0.045)		
ITA	0.000	0.943**	-0.033**	0.006	0.035**	0.028**	0.110**	0.069**	-0.174**	8.721	17.09
	(0.000)	(0.010)	(0.016)	(0.006)	(0.014)	(0.011)	(0.030)	(0.022)	(0.048)		
UK	0.874**	0.002**	0.085**	0.089**	0.025*	-0.094**	0.014	0.009	-0.024	10.14	24.46**
	(0.019)	(0.001)	(0.021)	(0.017)	(0.013)	(0.027)	(0.014)	(0.010)	(0.022)		
US	0.000	0.959**	-0.027	0.000	0.028**	0.005	0.061**	0.029**	-0.084**	6.534	4.444
	(0.000)	(0.014)	(0.020)	(0.001)	(0.010)	(0.013)	(0.015)	(0.011)	(0.022)		
UK	0.890**	4x10^{-3}	0.039**	0.094**	0.002	-0.027	0.001	0.010	-0.006	11.89	8.532
	(0.017)	(4x10^{-3})	(0.016)	(0.016)	(0.003)	(0.023)	(0.003)	(0.009)	(0.012)		
CAN	5x10^{-5}	0.962**	-0.015	0.001	0.026**	0.012**	0.003	0.017	-0.015	11.11	12.46
	(7x10^{-5})	(0.009)	(0.009)	(0.001)	(0.007)	(0.005)	(0.004)	(0.012)	(0.013)		
UK	0.917**	1x10^{-7}	0.001	0.077**	0.001	-0.013	0.000	0.000	0.000	11.59	11.58
	(0.014)	(4x10^{-6})	(0.011)	(0.014)	(0.001)	(0.011)	(0.002)	(0.003)	(0.002)		
JAP	3x10^{-3}	0.958**	0.013	4x10^{-8}	0.028**	-0.000	0.015	0.001	0.006	8.947	20.62*
	(1x10^{-3})	(0.013)	(0.020)	(1x10^{-5})	(0.012)	(0.011)	(0.012)	(0.006)	(0.027)		
UK	0.914**	9x10^{-6}	-0.006	0.069**	0.001	0.019*	0.008	0.007	-0.012	11.62	12.23
	(0.014)	(2x10^{-5})	(0.007)	(0.013)	(0.002)	(0.011)	(0.009)	(0.006)	(0.012)		
HK	9x10^{-6}	0.981**	-0.006	0.000	0.013**	0.003	0.007*	0.011*	-0.017**	14.43	10.10
	(3x10^{-5})	(0.005)	(0.009)	(0.001)	(0.004)	(0.004)	(0.004)	(0.006)	(0.008)		
UK	0.931**	3x10^{-3}	-0.032*	0.064**	0.000	0.011	0.005	0.014	-0.017	11.61	15.09
	(0.005)	(3x10^{-3})	(0.019)	(0.007)	(0.001)	(0.016)	(0.007)	(0.013)	(0.017)		
AUS	6x10^{-9}	0.915**	-0.000	1x10^{-6}	0.051**	0.001	0.013**	0.004	-0.015	6.787	28.94**
	(7x10^{-7})	(0.016)	(0.009)	(5x10^{-5})	(0.010)	(0.009)	(0.006)	(0.006)	(0.013)		
UK	0.857**	0.002	0.077	0.114**	0.007	-0.058	0.025	0.022	-0.046	10.82	7.723
	(0.035)	(0.002)	(0.053)	(0.029)	(0.012)	(0.054)	(0.021)	(0.025)	(0.044)		
DEV	0.000	0.978**	-0.039	0.002	0.022*	0.013*	0.043**	0.024*	-0.065**	53.61**	15.07
	(0.001)	(0.029)	(0.029)	(0.003)	(0.012)	(0.008)	(0.013)	(0.013)	(0.026)		
UK	0.915**	5x10^{-6}	-0.004	0.071**	6x10^{-6}	0.001	0.079**	0.050**	-0.127**	11.26	9.215
	(0.019)	(3x10^{-5})	(0.012)	(0.018)	(8x10^{-5})	(0.008)	(0.033)	(0.021)	(0.050)		
EUR	0.001	0.966**	-0.062**	0.014*	0.026**	0.039**	0.136**	0.064**	-0.187**	12.02	8.384
	(0.001)	(0.013)	(0.022)	(0.008)	(0.005)	(0.008)	(0.049)	(0.028)	(0.071)		
Panel B: Emerging Markets											
UK	0.935**	3x10^{-5}	-0.012*	0.057**	0.001	0.013**	0.001	0.001	-0.002	12.42	22.00**
	(0.010)	(4x10^{-5})	(0.007)	(0.009)	(0.000)	(0.004)	(0.002)	(0.002)	(0.004)		
RUS	7x10^{-4}	0.881**	0.016	0.001	0.099**	-0.018	0.007	0.007	0.013	32.20**	4.288
	(1x10^{-3})	(0.018)	(0.021)	(0.003)	(0.016)	(0.026)	(0.012)	(0.009)	(0.014)		
UK	0.908**	3x10^{-5}	-0.010	0.084**	0.000	-0.006	0.011	0.015**	-0.026*	11.87	10.13
	(0.015)	(5x10^{-5})	(0.009)	(0.016)	(0.000)	(0.012)	(0.009)	(0.008)	(0.014)		
POL	3x10^{-5}	0.952**	-0.009	0.000	0.028**	0.006	0.007	0.024	-0.025	19.75*	8.859
	(6x10^{-5})	(0.009)	(0.012)	(0.001)	(0.009)	(0.008)	(0.006)	(0.006)	(0.014)		
UK	0.913**	3x10^{-7}	-0.001	0.079**	2x10^{-6}	-0.001	0.009	0.008	-0.017	6.548	13.13
	(0.017)	(5x10^{-6})	(0.010)	(0.016)	(6x10^{-5})	(0.011)	(0.009)	(0.004)	(0.013)		
MEX	3x10^{-5}	0.951**	-0.015	0.001	0.039**	0.012	0.003	0.001	-0.004	5.212	35.82**
	(6x10^{-5})	(0.011)	(0.012)	(0.001)	(0.009)	(0.008)	(0.006)	(0.004)	(0.009)		
UK	0.909**	2x10^{-7}	-0.001	0.090**	0.001	-0.015*	0.000	0.000	-0.001	5.287	11.37
	(0.014)	(6x10^{-6})	(0.014)	(0.014)	(0.001)	(0.009)	(0.002)	(0.001)	(0.003)		
BRZ	1x10^{-3}	0.937**	-0.021	0.007	0.023**	0.025**	0.053	0.003	-0.025	5.238	19.71*
	(3x10^{-3})	(0.026)	(0.024)	(0.006)	(0.007)	(0.011)	(0.035)	(0.005)	(0.027)		
UK	0.930**	1x10^{-3}	-0.019*	0.059**	0.000	0.011*	0.009	0.011**	-0.019*	11.46	20.41*
	(0.010)	(1x10^{-3})	(0.011)	(0.010)	(0.001)	(0.006)	(0.008)	(0.004)	(0.011)		
IND	1x10^{-3}	0.835**	0.024*	0.002	0.119**	-0.035*	0.001	0.002	-0.003	29.67**	15.50
	(1x10^{-3})	(0.027)	(0.013)	(0.002)	(0.021)	(0.018)	(0.004)	(0.004)	(0.007)		
UK	0.931**	5x10^{-9}	0.000	0.068**	0.000	-0.006	0.003	0.004*	-0.006	5.184	7.041
	(0.010)	(1x10^{-6})	(0.016)	(0.011)	(0.000)	(0.008)	(0.005)	(0.002)	(0.006)		
CHI	3x10^{-6}	0.821**	-0.003	0.000	0.101**	-0.002	0.001	0.015	-0.007	17.03	12.86

	(2x10^{-5})	(0.037)	(0.010)	(0.000)	(0.022)	(0.013)	(0.008)	(0.014)	(0.013)		
UK	0.917**	1x10^{-5}	-0.008	0.074**	5x10^{-6}	0.001	0.004	0.003**	-0.007	11.95	13.37
	(0.012)	(2x10^{-5})	(0.005)	(0.012)	(3x10^{-5})	(0.004)	(0.005)	(0.001)	(0.005)		
TUR	0.000	0.909**	-0.035	0.005	0.065**	0.038	0.161**	0.161	-0.045	15.26	15.48
	(0.001)	(0.009)	(0.028)	(0.007)	(0.003)	(0.026)	(0.070)	(0.005)	(0.044)		
UK	0.922**	0.001	-0.067	0.070**	1x10^{-6}	0.001	0.005	0.002*	-0.007	11.71	14.41
	(0.010)	(0.002)	(0.049)	(0.010)	(2x10^{-5})	(0.006)	(0.006)	(0.001)	(0.005)		
EGY	0.003	0.911**	0.109	0.000	0.059**	-0.002	0.000	0.043**	-0.003	87.83**	55.71**
	(0.005)	(0.014)	(0.102)	(0.000)	(0.012)	(0.009)	(0.000)	(0.013)	(0.012)		
UK	0.932**	4x10^{-3}	-0.039**	0.072**	0.000	0.009	0.001	0.000	-0.000	11.56	9.091
	(0.012)	(4x10^{-3})	(0.019)	(0.011)	(0.001)	(0.010)	(0.002)	(0.000)	(0.002)		
SA	7x10^{-4}	0.857**	0.016	0.001	0.064**	0.017	0.034**	0.001	-0.013	33.26**	14.06
	(1x10^{-3})	(0.027)	(0.017)	(0.002)	(0.013)	(0.013)	(0.016)	(0.004)	(0.025)		
UK	0.943**	0.001	-0.048**	0.061**	0.001	0.015	0.000	0.001	-0.001	11.72	12.96
	(0.012)	(0.001)	(0.021)	(0.011)	(0.002)	(0.012)	(0.002)	(0.004)	(0.006)		
EM	7x10^{-6}	0.877**	0.005	0.001	0.052**	0.015	0.025**	0.001	-0.010	155.0**	26.86**
	(4x10^{-5})	(0.027)	(0.013)	(0.002)	(0.013)	(0.013)	(0.012)	(0.004)	(0.017)		
Panel C: Frontier Markets											
UK	0.919**	7x10^{-6}	-0.005	0.077**	9x10^{-6}	0.002	0.000	0.002	-0.001	11.99	10.12
	(0.012)	(2x10^{-5})	(0.006)	(0.012)	(5x10^{-5})	(0.006)	(0.001)	(0.001)	(0.004)		
ARG	1x10^{-3}	0.919**	0.019	0.001	0.058**	-0.013	0.008	0.000	-0.002	13.98	8.827
	(3x10^{-3})	(0.017)	(0.024)	(0.002)	(0.012)	(0.021)	(0.013)	(0.001)	(0.011)		
UK	0.913**	5x10^{-6}	-0.004	0.117**	0.001	0.016	0.002	0.001	-0.002	11.52	6.510
	(0.013)	(2x10^{-5})	(0.011)	(0.019)	(0.001)	(0.018)	(0.005)	(0.002)	(0.006)		
JAM	3x10^{-6}	0.952**	-0.003	0.000	0.029**	0.003	0.000	0.016**	0.002	57.47**	9.634
	(8x10^{-6})	(0.010)	(0.004)	(0.000)	(0.007)	(0.003)	(0.000)	(0.008)	(0.004)		
UK	0.949**	1x10^{-3}	-0.021	0.054**	0.000	0.005	0.000	0.000	-0.000	12.44	39.38**
	(0.008)	(2x10^{-3})	(0.014)	(0.009)	(0.000)	(0.005)	(0.002)	(0.001)	(0.003)		
ROM	7x10^{-4}	0.609**	0.013	0.001	0.271**	-0.029	0.017	0.000	0.001	28.96**	6.053
	(3x10^{-3})	(0.046)	(0.023)	(0.003)	(0.041)	(0.054)	(0.029)	(0.006)	(0.142)		
UK	0.928**	1x10^{-5}	0.006	0.078**	0.000	-0.003	0.001	3x10^{-7}	-0.000	12.44	39.38**
	(0.011)	(4x10^{-5})	(0.013)	(0.013)	(0.000)	(0.007)	(0.003)	(1x10^{-5})	(0.001)		
UKR	0.001	0.727**	-0.044*	0.006	0.117**	0.051	0.139**	0.168**	-0.305**	28.96**	6.053
	(0.001)	(0.075)	(0.024)	(0.007)	(0.039)	(0.036)	(0.048)	(0.056)	(0.084)		
UK	0.924**	2x10^{-6}	-0.002	0.090**	0.001	-0.022**	0.005	0.001	-0.005	11.50	11.46
	(0.011)	(2x10^{-5})	(0.017)	(0.014)	(0.001)	(0.011)	(0.006)	(0.002)	(0.006)		
KEN	1x10^{-6}	0.709**	0.002	0.000	0.093**	-0.004	0.001	0.178**	0.032	88.12**	1.029
	(2x10^{-5})	(0.036)	(0.008)	(0.000)	(0.019)	(0.009)	(0.003)	(0.029)	(0.036)		
UK	0.928**	1x10^{-3}	0.027	0.072**	0.000	-0.007	0.003	0.000	-0.002	11.70	15.17
	(0.012)	(4x10^{-3})	(0.025)	(0.012)	(0.001)	(0.010)	(0.004)	(0.001)	(0.003)		
NIG	5x10^{-7}	0.612**	-0.001	0.000	0.179**	-0.007	0.005	0.229**	0.069**	132.2**	9.423
	(9x10^{-6})	(0.041)	(0.010)	(0.000)	(0.028)	(0.015)	(0.005)	(0.042)	(0.031)		
UK	0.944**	1x10^{-5}	-0.007	0.055**	0.000	0.004	0.000	0.000	-0.000	5.409	24.62**
	(0.008)	(5x10^{-5})	(0.014)	(0.008)	(0.000)	(0.006)	(0.002)	(0.000)	(0.000)		
PAK	6x10^{-4}	0.668**	-0.013	0.000	0.283**	0.021	0.000	0.000	-0.000	34.69**	2.253
	(1x10^{-3})	(0.033)	(0.014)	(0.001)	(0.034)	(0.029)	(0.001)	(0.005)	(0.004)		
UK	0.925**	0.000	-0.020	0.088**	0.000	0.010	0.000	0.000	-0.000	11.50	11.65
	(0.011)	(0.000)	(0.015)	(0.012)	(0.000)	(0.008)	(0.001)	(0.001)	(0.001)		
SRL	0.001	0.590**	0.037**	0.002	0.315**	-0.052**	0.023*	0.009	0.028	6.702	0.009
	(0.000)	(0.028)	(0.013)	(0.002)	(0.039)	(0.024)	(0.013)	(0.020)	(0.032)		
UK	0.911**	1x10^{-5}	-0.007	0.096**	0.002	0.028*	0.000	0.002	0.002	12.10	6.179
	(0.018)	(5x10^{-5})	(0.012)	(0.021)	(0.002)	(0.015)	(0.002)	(0.003)	(0.006)		
FM	6x10^{-6}	0.964**	-0.000	6x10^{-6}	0.019**	-0.001	0.000	0.015**	-0.003	38.44**	42.42**
	(5x10^{-5})	(0.010)	(0.005)	(5x10^{-5})	(0.008)	(0.003)	(0.001)	(0.007)	(0.005)		

Note: The '**' and '*' denote significant levels at 5% and 10%, respectively. Standard errors are reported in parenthesis.

Table 3.4: Great Austerity – Asymmetric BEKK (*1,1*)

$$h_{11,t} = c_{11} + \left(\alpha_{11}^2\varepsilon_{11,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{21}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1}\right) + \left(\delta_{11}^2\eta_{11,t-1}^2 + 2\delta_{11}\delta_{21}\eta_{11,t-1}\eta_{22,t-1} + \delta_{21}^2\eta_{22,t-1}^2\right)$$

$$h_{22,t} = c_{22} + \left(\alpha_{12}^2\varepsilon_{11,t-1}^2 + 2\alpha_{12}\alpha_{22}\varepsilon_{11,t-1}\varepsilon_{22,t-1} + \alpha_{22}^2\varepsilon_{22,t-1}^2\right) + \left(\beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1}\right) + \left(\delta_{12}^2\eta_{11,t-1}^2 + 2\delta_{12}\delta_{22}\eta_{11,t-1}\eta_{22,t-1} + \delta_{22}^2\eta_{22,t-1}^2\right)$$

	$h_{11,t-1}$	$h_{22,t-1}$	$h_{12,t-1}$	$\varepsilon_{11,t-1}^2$	$\varepsilon_{22,t-1}^2$	$\varepsilon_{11,t-1}\varepsilon_{22,t-1}$	$\eta_{11,t-1}^2$	$\eta_{22,t-1}^2$	$\eta_{11,t-1}\eta_{22,t-1}$	Q(12)	$Q^2(12)$
Panel A: Developed Markets											
UK	0.886**	7×10^{-4}	0.016	0.102**	0.000	-0.009	0.003	0.005	-0.007	5.870	8.472
	(0.029)	(2×10^{-3})	(0.024)	(0.027)	(0.001)	(0.024)	(0.010)	(0.009)	(0.019)		
GER	9×10^{-4}	0.918**	-0.019	0.003	0.066**	0.026	0.005	0.001	-0.005	5.499	14.77
	(3×10^{-3})	(0.029)	(0.033)	(0.005)	(0.022)	(0.020)	(0.014)	(0.006)	(0.018)		
UK	0.876**	1×10^{-4}	0.023	0.125**	0.002	-0.034	0.006	0.008	-0.014	5.749	8.816
	(0.031)	(2×10^{-3})	(0.025)	(0.004)	(0.004)	(0.033)	(0.016)	(0.012)	(0.027)		
FRA	0.001	0.957**	-0.072*	0.028	0.025	0.054**	0.011	0.004	-0.014	8.581	14.96
	(0.002)	(0.034)	(0.043)	(0.022)	(0.017)	(0.009)	(0.025)	(0.012)	(0.034)		
UK	0.881**	1×10^{-4}	0.023**	0.116**	0.002	-0.029*	0.001	4×10^{-7}	0.000	5.665	10.40
	(0.019)	(2×10^{-3})	(0.010)	(0.023)	(0.001)	(0.016)	(0.004)	(5×10^{-5})	(0.002)		
ITA	0.001	0.955**	-0.058**	0.012	0.041**	0.044**	0.006	0.008	0.023	7.947	11.36
	(0.001)	(0.016)	(0.025)	(0.009)	(0.013)	(0.013)	(0.013)	(0.011)	(0.023)		
UK	0.442*	0.072**	0.358**	0.167**	0.242**	-0.402**	0.033	0.000	-0.007	5.366	23.03**
	(0.073)	(0.024)	(0.038)	(0.045)	(0.057)	(0.092)	(0.032)	(0.004)	(0.045)		
US	0.027	1.084**	-0.339**	0.060**	0.002	0.025	0.024	0.031	-0.055	11.55	14.36
	(0.016)	(0.060)	(0.113)	(0.018)	(0.004)	(0.018)	(0.020)	(0.028)	(0.044)		
UK	0.886**	2×10^{-3}	-0.025	-0.024	0.038	0.034	0.071**	0.023	-0.074*	5.960	13.76
	(0.025)	(5×10^{-3})	(0.032)	(0.032)	(0.024)	(0.032)	(0.016)	(0.015)	(0.042)		
CAN	1×10^{-6}	0.922**	-0.002	0.004	0.087	-0.035	0.023	0.002	-0.034	11.29	28.68**
	(5×10^{-5})	(0.021)	(0.040)	(0.008)	(0.039)	(0.039)	(0.016)	(0.007)	(0.027)		
UK	0.892**	3×10^{-4}	-0.011	0.099**	0.000	-0.005	0.001	0.003	-0.003	6.076	8.741
	(0.018)	(2×10^{-3})	(0.027)	(0.027)	(0.000)	(0.018)	(0.002)	(0.003)	(0.006)		
JAP	0.005	0.848**	0.128**	0.022	0.073**	-0.079	0.072*	0.005	-0.039	4.889	35.91**
	(0.004)	(0.036)	(0.036)	(0.023)	(0.017)	(0.049)	(0.039)	(0.009)	(0.041)		
UK	0.879**	6×10^{-7}	0.001	0.098**	2×10^{-7}	-0.000	0.007	0.027**	-0.028	5.838	7.041
	(0.021)	(1×10^{-5})	(0.016)	(0.022)	(4×10^{-5})	(0.023)	(0.007)	(0.011)	(0.018)		
HK	2×10^{-3}	0.945**	-0.022	0.005	0.035**	0.027	0.054**	0.003	-0.026	10.51	17.03
	(4×10^{-3})	(0.013)	(0.037)	(0.008)	(0.010)	(0.017)	(0.023)	(0.005)	(0.025)		
UK	1.040**	0.023**	-0.312**	0.009	0.013**	0.021**	0.000	0.000	-0.000	6.206	14.28
	(0.022)	(0.010)	(0.073)	(0.006)	(0.006)	(0.008)	(0.001)	(0.001)	(0.001)		
AUS	0.068**	0.309**	0.289**	0.384**	0.058**	-0.298**	0.001	0.005	-0.004	6.757	19.78*
	(0.013)	(0.072)	(0.025)	(0.054)	(0.017)	(0.048)	(0.007)	(0.025)	(0.027)		
UK	0.565**	0.054**	0.348**	0.287**	0.241**	-0.526**	0.058	0.012	-0.053	5.852	24.16**
	(0.051)	(0.017)	(0.042)	(0.061)	(0.068)	(0.122)	(0.046)	(0.026)	(0.076)		
DEV	0.022**	1.177**	-0.324**	0.123**	0.017	-0.091**	0.002	0.006	-0.006	27.56**	21.29**
	(0.008)	(0.052)	(0.068)	(0.026)	(0.014)	(0.046)	(0.006)	(0.013)	(0.017)		
UK	0.862**	4×10^{-3}	0.038*	0.142**	0.005	-0.056*	0.003	0.005	-0.008	5.744	9.450
	(0.027)	(5×10^{-3})	(0.021)	(0.033)	(0.005)	(0.033)	(0.009)	(0.009)	(0.019)		
EUR	0.002	0.968**	-0.082**	0.027	0.027*	0.054**	0.002	0.001	-0.003	7.032	16.32
	(0.001)	(0.028)	(0.035)	(0.017)	(0.015)	(0.007)	(0.008)	(0.005)	(0.013)		
Panel B: Emerging Markets											
UK	0.902**	4×10^{-6}	-0.004	0.085**	0.000	0.012*	0.003	0.000	-0.002	5.795	8.737
	(0.015)	(9×10^{-6})	(0.005)	(0.016)	(0.000)	(0.006)	(0.005)	(0.001)	(0.004)		
RUS	0.001	0.949**	-0.068**	0.009	0.052**	0.044**	0.032	0.004	-0.024	21.91**	10.33
	(0.001)	(0.010)	(0.023)	(0.007)	(0.009)	(0.016)	(0.029)	(0.006)	(0.026)		
UK	0.880**	9×10^{-4}	0.019	0.095**	0.000	0.004	0.002	0.007	-0.007	5.689	7.362
	(0.019)	(1×10^{-3})	(0.013)	(0.019)	(0.000)	(0.014)	(0.004)	(0.009)	(0.013)		
POL	0.001	0.973**	-0.056**	0.008	0.029**	0.030**	0.019*	0.007	-0.023	16.93	17.74
	(0.001)	(0.012)	(0.018)	(0.005)	(0.009)	(0.007)	(0.012)	(0.008)	(0.019)		
UK	1.048**	0.021**	-0.294**	0.113**	0.018*	-0.091**	0.004	0.025**	-0.021	5.459	12.59
	(0.025)	(0.005)	(0.039)	(0.020)	(0.010)	(0.031)	(0.007)	(0.013)	(0.019)		
MEX	0.033**	0.728**	0.309**	0.022**	0.079**	-0.083**	0.008	0.001	-0.005	19.76*	42.14**
	(0.007)	(0.027)	(0.028)	(0.016)	(0.016)	(0.022)	(0.011)	(0.003)	(0.012)		
UK	0.889**	9×10^{-4}	0.018	0.093**	0.000	-0.009	0.004	0.005	-0.008	5.837	10.12
	(0.019)	(2×10^{-3})	(0.015)	(0.019)	(0.001)	(0.016)	(0.006)	(0.004)	(0.009)		
BRZ	0.000	0.940**	-0.039	0.004	0.043**	0.027	0.051*	0.004	-0.028	5.643	31.99**
	(0.001)	(0.018)	(0.032)	(0.006)	(0.012)	(0.018)	(0.029)	(0.007)	(0.031)		
UK	0.924**	0.020**	-0.275**	0.038**	0.019**	0.054**	0.016	0.023**	-0.037**	5.544	22.57**
	(0.025)	(0.003)	(0.019)	(0.011)	(0.009)	(0.012)	(0.009)	(0.010)	(0.017)		
IND	0.052**	0.842**	0.418**	0.051**	0.051**	-0.076**	0.008	0.000	-0.002	18.53	18.24
	(0.007)	(0.019)	(0.028)	(0.014)	(0.014)	(0.016)	(0.013)	(0.001)	(0.008)		
UK	0.877**	3×10^{-5}	0.010	0.115**	6×10^{-5}	-0.002	0.002	0.009*	-0.009	5.521	6.349
	(0.016)	(6×10^{-5})	(0.010)	(0.018)	(1×10^{-3})	(0.015)	(0.004)	(0.005)	(0.009)		
CHI	0.000		-0.031*	0.002		0.012	0.014	0.001	0.009	21.64**	17.79

	(0.000)	0.971**	(0.017)	(0.002)	0.021**	(0.007)	(0.009)	(0.003)	(0.009)		
		(0.007)			(0.005)						
UK	0.889**	8×10^{-6}	0.005	0.093**	0.000	0.007	0.000	0.001	0.000	5.657	7.358
	(0.019)	(4×10^{-5})	(0.012)	(0.017)	(0.000)	(0.009)	(0.001)	(0.002)	(0.002)		
TUR	0.000	0.938**	-0.035	0.008	0.042**	0.036**	0.011	0.000	0.002	13.99	11.19
	(0.001)	(0.023)	(0.031)	(0.008)	(0.012)	(0.015)	(0.015)	(0.001)	(0.011)		
UK	0.898**	0.000	0.039	0.089**	0.001	-0.018	0.000	0.001	-0.001	6.025	11.78
	(0.015)	(0.001)	(0.027)	(0.014)	(0.001)	(0.013)	(0.001)	(0.002)	(0.003)		
EGY	0.000	0.718**	-0.035	0.025	0.144**	0.119**	0.137**	0.017	-0.095*	50.25**	2.357
	(0.001)	(0.045)	(0.033)	(0.019)	(0.025)	(0.049)	(0.050)	(0.016)	(0.056)		
UK	0.918**	0.000	-0.037	0.053**	0.009	0.043**	0.025*	0.043**	-0.066**	6.123	9.036
	(0.029)	(0.001)	(0.038)	(0.012)	(0.012)	(0.020)	(0.014)	(0.020)	(0.032)		
SA	7×10^{-4}	0.899**	0.016	0.001	0.088**	-0.023	0.049**	0.019	-0.061	11.45	13.58
	(3×10^{-3})	(0.028)	(0.033)	(0.004)	(0.025)	(0.035)	(0.022)	(0.017)	(0.039)		
UK	0.598**	0.055**	0.364**	0.095**	0.061**	-0.152**	0.006	0.003	0.008	7.037	37.15**
	(0.041)	(0.014)	(0.034)	(0.024)	(0.019)	(0.035)	(0.009)	(0.007)	(0.006)		
EM	0.049**	1.152**	-0.474**	0.095**	0.000	0.011	0.014	0.012	-0.026	77.83**	4.682
	(0.013)	(0.036)	(0.067)	(0.024)	(0.002)	(0.027)	(0.016)	(0.015)	(0.029)		
Panel C: Frontier Markets											
UK	0.896**	3×10^{-6}	0.000	0.104**	0.000	-0.008	0.002	0.000	-0.001	5.860	8.459
	(0.015)	(1×10^{-5})	(0.006)	(0.016)	(0.000)	(0.007)	(0.004)	(0.000)	(0.002)		
ARG	5×10^{-3}	0.941**	-0.042*	0.011	0.025**	0.033**	0.099	0.058**	-0.151**	15.23	57.55**
	(5×10^{-3})	(0.014)	(0.023)	(0.009)	(0.009)	(0.012)	(0.035)	(0.019)	(0.046)		
UK	0.893**	9×10^{-7}	0.002	0.132**	8×10^{-6}	-0.002	0.000	0.000	-0.001	5.719	6.098
	(0.016)	(4×10^{-5})	(0.044)	(0.023)	(1×10^{-5})	(0.025)	(0.001)	(0.002)	(0.002)		
JAM	2×10^{-3}	0.703**	0.024**	0.001	0.039**	-0.009	0.004	0.219**	0.065**	11.08	2.217
	(2×10^{-3})	(0.057)	(0.011)	(0.001)	(0.019)	(0.008)	(0.004)	(0.050)	(0.027)		
UK	0.892**	2×10^{-5}	0.008	0.086**	1×10^{-6}	-0.001	0.004	0.021**	-0.019	5.431	13.26
	(0.016)	(9×10^{-5})	(0.019)	(0.016)	(6×10^{-5})	(0.019)	(0.005)	(0.009)	(0.015)		
ROM	0.002*	0.896**	-0.083**	0.017*	0.086**	0.077**	0.027	0.011	-0.034	15.97	23.88**
	(0.001)	(0.027)	(0.024)	(0.010)	(0.024)	(0.019)	(0.021)	(0.021)	(0.040)		
UK	0.914**	2×10^{-3}	0.026	0.076**	8×10^{-5}	-0.005	0.000	0.000	0.000	5.796	18.54
	(0.009)	(3×10^{-3})	(0.018)	(0.009)	(3×10^{-4})	(0.009)	(0.001)	(0.001)	(0.001)		
UKR	9×10^{-4}	0.679**	-0.016	0.031	0.192**	0.153**	0.076*	0.072*	-0.148**	131.9**	12.23
	(2×10^{-3})	(0.053)	(0.016)	(0.019)	(0.030)	(0.054)	(0.042)	(0.044)	(0.072)		
UK	0.909**	0.009	0.178**	0.078**	0.009	-0.053**	0.000	0.009	0.001	5.428	9.443
	(0.012)	(0.006)	(0.056)	(0.011)	(0.007)	(0.019)	(0.000)	(0.009)	(0.006)		
KEN	0.001*	0.525**	-0.049**	0.009**	0.263**	0.099**	0.067**	0.079*	-0.147**	165.1**	3.484
	(0.006)	(0.045)	(0.014)	(0.004)	(0.035)	(0.022)	(0.014)	(0.041)	(0.044)		
UK	0.919**	0.003*	0.113**	0.067**	0.007	-0.042**	0.001	0.006	-0.005	6.330	18.38
	(0.009)	(0.002)	(0.032)	(0.009)	(0.004)	(0.014)	(0.002)	(0.007)	(0.007)		
NIG	1×10^{-4}	0.610**	-0.017	0.003	0.304**	0.062**	0.001	0.033	-0.012	189.1**	7.792
	(2×10^{-4})	(0.044)	(0.014)	(0.002)	(0.041)	(0.023)	(0.010)	(0.031)	(0.056)		
UK	0.917**	2×10^{-4}	0.028	0.068**	0.001	-0.015	0.002	0.043**	-0.019	5.428	24.72**
	(0.009)	(2×10^{-4})	(0.019)	(0.009)	(0.001)	(0.012)	(0.004)	(0.012)	(0.018)		
PAK	9×10^{-8}	0.839**	-0.001	2×10^{-6}	0.169**	0.001	6×10^{-6}	0.000	0.000	36.03**	2.233
	(1×10^{-6})	(0.017)	(0.004)	(2×10^{-5})	(0.021)	(0.005)	(5×10^{-5})	(0.001)	(0.000)		
UK	0.908**	0.000	-0.034	0.086**	0.000	0.009	0.004	0.027**	-0.019	11.50	11.65
	(0.013)	(0.001)	(0.031)	(0.013)	(0.001)	(0.018)	(0.005)	(0.013)	(0.015)		
SRL	8×10^{-6}	0.806**	0.005	2×10^{-6}	0.151**	-0.001	0.026**	0.010	-0.032	6.702	0.009
	(4×10^{-5})	(0.032)	(0.013)	(6×10^{-5})	(0.025)	(0.014)	(0.011)	(0.013)	(0.025)		
UK	0.901**	0.000	0.040	0.096**	0.006	-0.047	0.000	0.005	-0.001	5.839	13.64
	(0.017)	(0.001)	(0.026)	(0.007)	(0.007)	(0.032)	(0.001)	(0.016)	(0.007)		
FM	1×10^{-3}	0.944**	-0.019**	0.001	0.042**	0.015**	0.000	0.000	0.000	75.34**	20.07*
	(9×10^{-4})	(0.011)	(0.009)	(0.001)	(0.008)	(0.006)	(0.002)	(0.001)	(0.002)		

Notes: The '**' and '*' denote significant levels at 5% and 10%, respectively. Standard errors are reported in parenthesis.

Table 3.5: Summary of Volatility and Shock Spillovers

	Great Moderation		Great Austerity	
	Volatility Spillover	Shock Spillover	Volatility Spillover	Shock Spillover
Panel A: Developed Markets				
Germany	Unidirectional			
France	Unidirectional	Bidirectional	Unidirectional	Unidirectional
Italy	Bidirectional	Unidirectional	Bidirectional	Bidirectional
US	Unidirectional	Unidirectional	Bidirectional	Unidirectional
Canada	Unidirectional	Unidirectional		
Japan			Unidirectional	
Hong Kong		Unidirectional		
Australia	Unidirectional		Bidirectional	Bidirectional
Developed		Unidirectional	Bidirectional	Bidirectional
Euro Area	Unidirectional	Unidirectional	Bidirectional	Bidirectional
Panel B: Emerging Markets				
Russia	Unidirectional	Unidirectional	Unidirectional	Bidirectional
Poland			Unidirectional	Unidirectional
Mexico			Bidirectional	Bidirectional
Brazil		Bidirectional		
India	Bidirectional	Bidirectional	Bidirectional	Bidirectional
China			Unidirectional	
Turkey				Unidirectional
Egypt			Unidirectional	Unidirectional
South Africa	Unidirectional			Unidirectional
Emerging	Unidirectional		Bidirectional	Unidirectional
Panel C: Frontier Markets				
Argentina			Unidirectional	Unidirectional
Jamaica			Unidirectional	
Romania			Unidirectional	Unidirectional
Ukraine	Unidirectional			Unidirectional
Kenya		Unidirectional	Bidirectional	Bidirectional
Nigeria			Unidirectional	Bidirectional
Pakistan				
Sri Lanka	Unidirectional	Unidirectional		
Frontier		Unidirectional	Unidirectional	Unidirectional

Notes: This table summarises the shock and volatility spillover effects between UK and other foreign markets. No significant cross-market effects is represented as blank, significant unilateral transmission effect is shown as unidirectional, and significant feedback transmission effect is represented as bidirectional.

3.5.2 Return, Risk and Correlation Analysis

The decisions on optimal asset allocation and risk hedging are dependent on variances, covariances and correlations. Table 3.6 displays the two sample *t*-test for equality of time-varying conditional correlations, conditional standard deviations and expected returns between the UK and partner economies over the GM and GA periods.[67] In general, the *t*-tests for equality of means in the stock correlation between GM and GA indicates that we reject the null hypothesis that the mean correlation are the same for all diversified markets except for UK/Japan. The mean difference in correlation between GM and GA periods is positively significant for all diversified portfolios with the exception of UK/Japan, UK/India, UK/Kenya and UK/Sri Lanka. This suggests that correlation coefficients have significantly increased in GA period between the UK and most foreign stock markets, thereby reducing potential portfolio diversification benefits. Similarly, the equality of variance test indicates that we reject the null that the standard deviation (portfolio risk) are the same in all markets, except for UK/Euro Area portfolio. The portfolio risk during GA period exceed the GM in all markets except for UK/Turkey, UK/Pakistan and UK/Sri Lanka. The equality of portfolio returns between GM and GA periods indicates that we cannot reject the null hypothesis that the portfolio returns are the same in most diversified markets. Thus, there is more potential portfolio diversification benefit in GM period than GA.

Figure 3.4 demonstrates the time varying conditional correlation, portfolio volatility and portfolio return between the UK and foreign stock markets. All the markets depict significant spikes in portfolio risk during the 2008 September stock market crash. It is also apparent that relatively low volatility dominates the GM period while high volatility persists in GA period. The average correlation between UK and three largest European markets tends to be significantly higher during the GA period (France [0.88], Germany [0.85] and Italy [0.77]) than GM period (0.82, 0.75 and 0.76). The correlation between UK and France is higher than other markets in both periods suggesting that geographically contiguous markets have higher integration. At the same time, the portfolio risk has increased in GA period in these markets. This reinforces previous findings that correlation between two countries in the same region tends to be higher than two countries in different region (see Pretorius, 2002; Flavin *et al*. 2002; Lucey and Zhang, 2010). The significant increases in correlation and portfolio risk suggest considerable low diversification benefits between the UK and Western European countries.

[67] Portfolio risk is rescaled by multiplying the values by 10 for the sake of having a presentable graph.

Furthermore, stock correlations between the UK and the Pacific countries tend to be significantly higher during GA period (US [0.59], Canada [0.54], Australia [0.32], and Hong Kong [0.37]) than GM period (US [0.42], Canada [0.46], Australia [0.25], and Hong Kong [0.30]). By the same token, portfolio risk has increased in these markets and the portfolio returns are not significantly different from zero. This pattern of results demonstrates marginal fall in potential diversification benefits between the UK and Pacific markets except Japan that indicates otherwise. However, there are more potential diversification benefits between UK and Pacific markets than between UK and Western European markets.

Additionally, the stock correlations between UK and Eastern European markets tend to be significantly higher during GA period (Poland [0.59], Russia [0.56], Romania [0.34], and Ukraine [0.25]) than GM period (Poland [0.35], Russia [0.32], Romania [0.02], and Ukraine [0.01]). Especially, stock correlations between UK and Eurozone countries market (Poland) are higher than non-Eurozone countries (Russia, Romania and Ukraine). This suggests that Eurozone markets are more integrated with the UK than non-Eurozone countries. The portfolio risk of these markets has increased and the portfolio returns are not significantly different from zero. There is a significant increase in correlation, higher portfolio risk and negative portfolio return for these markets except UK/Poland, suggesting a reduction in potential diversification benefits during the GA period. Overall, stock market integration has intensified very rapidly between UK and Eastern European markets due to financial liberalisation and economic deregulation.

The stock correlations between UK and Latin American markets are significantly higher during GA period (Mexico [0.51], Brazil [0.49] and Argentina [0.23]) than GM period (Mexico [0.40], Brazil [0.32] and Argentina [0.23]). The stock correlation between UK and Jamaica is significantly low at an average of 0.02 suggesting huge potential gains from portfolio diversification although the market is one of the least mature. The portfolio risk increases for these markets and their portfolio returns are not significantly different from zero in the GA period. The increase in correlation, higher portfolio risk and insignificant positive portfolio return indicate less diversification benefits to be derived.

For Asian stock markets, stock correlations tend to be significantly higher during GA period (Turkey [0.47], China [0.15] and Pakistan [0.06]) than GM period (Turkey [0.22], China [-0.03] and Pakistan [0.04]). Whereas, stock correlation between UK and India/Sri Lanka significantly decline from 0.19/0.08 during GM period to 0.15/0.06 during GA period. The portfolio risk of UK investors that holds Asian stocks in both periods is the same for India, significantly reduce for Turkey, Pakistan and Sri Lanka while it increases for China. The portfolio returns for these markets are not significantly different from zero. Largely, the reduction in correlation, lower portfolio risk and positive portfolio returns in India and Sri Lanka suggests increase in potential diversification benefits unlike the reduced diversification benefits for UK/China. However, the Sri Lanka and Pakistan markets are significantly segmented from the UK market.

In another case, stock correlations between UK and African markets are significantly higher during GA period (South Africa [0.67], Egypt [0.19] and Nigeria [0.06]) than GM period (South Africa [0.43], Egypt [0.02] and Nigeria [0.01]). In contrast, the correlation between UK and Kenya significantly decline from 0.003 during GM period to -0.034 during GA period. The portfolio risk for UK/South Africa, UK/Egypt and UK/Nigeria increases while it stays the same for UK/Kenya. In a similar vein, the portfolio returns are significantly different from zero. The significant increase in correlation, higher portfolio and lower portfolio return suggest limited potential diversification benefits except for UK/Kenya. However, the Kenyan, Nigerian and Egyptian stock markets appears to be highly segmented from the UK market.

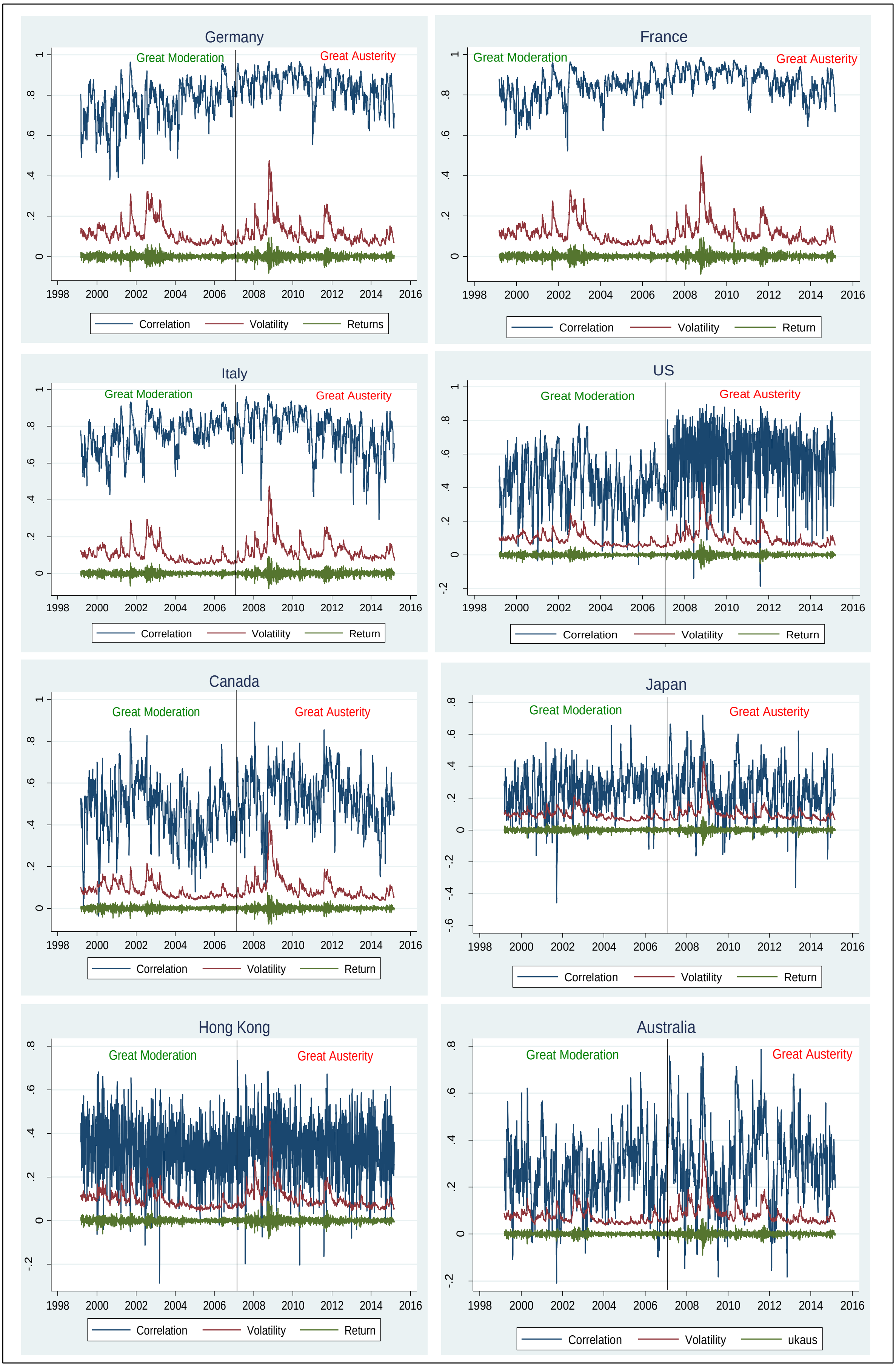
For specialised markets, the stock correlations between UK and MSCI developed/emerging/frontier markets are higher during the GA period (0.87, 0.79, 0.63 and 0.29) than the GM period (0.82, 0.65, 0.44 and 0.02). These trends demonstrate significant decline in potential diversification benefits. However, there are significant benefit for UK investors to gain diversifying into frontier and emerging markets. The portfolio risk for these markets has increased significantly while their portfolio returns are not statistically different from zero. Overall, the increase in correlation, increase in portfolio risk and lower positive returns suggests limited potential diversification benefits in these markets except for MSCI developed markets that have higher returns in GA period.

In summary, increase correlation, higher portfolio risk and lower return between UK and foreign markets suggest that diversification benefits have reduced on average during GA period for all markets with the exception of UK/Japan, UK/India, UK/Kenya and UK/Sri Lanka. This is consistent with previous finding that correlation is higher during volatile times (Longin and Solnik, 1995; You and Diagler, 2010). Largely, UK investors will benefit more by diversifying into emerging and frontier markets because of higher returns, and relatively lower volatilities and correlations. Particularly, the linkage between UK and frontier markets exhibits low correlation, minimal portfolio risk and considerable portfolio returns which is an indication of substantial potential benefits from portfolio diversification. By including frontier market equities in an international portfolio selection, a UK investor can achieve higher expected returns with significant risk reduction. This corroborates with the finding that frontier markets have low integration with the world market and offer diversification benefits (see Speidell and Krohne, 2007; Jayasuriya and Shambora, 2009; Berger *et al.,* 2011).

Table 3.6: Equality Tests for Return, Volatility and Correlation

	Equality of mean (Portfolio Return)				**Equality of variance (Portfolio risk)**				**Equality of mean (Time-varying Correlation)**			
Markets	**GM ($*10^{-3}$)**	**GA ($*10^{-3}$)**	**Diff ($*10^{-3}$)**	**t-stat**	**GM**	**GA**	**Combined**	**t-stat**	**GM**	**GA**	**Diff Mean**	**t-stat**
Germany	0.004	0.087	-0.083	-0.222	0.010	0.010	0.010	0.784**	0.748	0.849	0.010	35.55**
France	0.002	0.039	-0.038	-0.098	0.010	0.011	0.010	0.753**	0.818	0.879	0.061	27.59**
Italy	0.012	-0.245	0.257	0.586	0.010	0.012	0.011	0.849**	0.757	0.774	0.018	4.695**
US	0.013	0.124	-0.112	-0.337	0.008	0.009	0.009	0.548**	0.423	0.592	0.169	37.04**
Canada	0.184	0.076	0.109	0.346	0.009	0.009	0.009	0.370**	0.462	0.542	0.081	21.89**
Japan	0.012	0.061	-0.049	-0.149	0.008	0.009	0.009	0.554**	0.249	0.243	-0.006	-1.432
Hong Kong	0.105	0.084	0.021	0.062	0.009	0.009	0.009	0.481**	0.304	0.369	0.065	18.18**
Australia	0.221	0.043	0.179	0.656	0.007	0.008	0.008	0.347**	0.248	0.324	0.077	14.45**
Developed	0.037	0.082	-0.045	-0.136	0.009	0.010	0.009	0.561**	0.647	0.791	0.144	58.93**
Euro Area	0.046	-0.003	0.049	0.116	0.011	0.011	0.011	0.965	0.823	0.866	0.043	18.77**
Russia	0.193	-0.271	0.465	0.866	0.009	0.013	0.011	0.363**	0.319	0.557	0.238	45.49 **
Poland	0.223	0.063	0.161	0.468	0.009	0.010	0.009	0.394**	0.348	0.591	0.243	53.91**
Mexico	0.261	0.157	0.105	0.309	0.009	0.009	0.009	0.699**	0.404	0.506	0.102	26.75**
Brazil	0.119	0.075	0.043	0.118	0.009	0.009	0.009	0.627**	0.322	0.491	0.168	42.74**
India	0.193	0.225	-0.032	-0.102	0.008	0.008	0.008	0.597**	0.199	0.146	-0.054	-11.49**
China	0.183	0.069	0.114	0.374	0.007	0.009	0.008	0.373**	-0.025	0.154	0.179	43.03**
Turkey	0.415	0.183	0.232	0.573	0.009	0.010	0.010	0.515**	0.218	0.474	0.256	39.69**
Egypt	0.381	0.119	0.261	0.766	0.008	0.008	0.008	0.451**	0.019	0.193	0.173	35.23**
South Afr.	0.058	0.186	-0.129	-0.368	0.009	0.010	0.010	0.755**	0.434	0.672	0.238	66.37**
Emerging	0.462	0.067	0.396	1.159	0.009	0.010	0.010	0.226**	0.444	0.631	0.188	59.32**
Argentina	0.179	0.138	0.041	0.113	0.009	0.010	0.010	0.525**	0.231	0.440	0.209	35.18**
Jamaica	0.455	-0.008	0.463	2.279**	0.007	0.007	0.007	0.789**	0.023	0.031	0.008	2.300**
Romania	0.599	0.034	0.565	1.669*	0.008	0.009	0.009	0.286**	0.017	0.336	0.319	59.70**
Ukraine	0.718	-0.029	0.747	2.165**	0.008	0.009	0.009	0.387**	0.003	0.252	0.256	49.85**
Kenya	0.163	0.032	0.131	0.573	0.007	0.006	0.007	0.529**	0.003	-0.034	-0.037	-7.995**
Nigeria	0.531	-0.044	0.576	2.408**	0.007	0.007	0.007	0.613**	0.004	0.056	0.052	11.09**
Pakistan	0.505	0.315	0.190	0.671	0.008	0.008	0.008	1.485**	0.038	0.061	0.022	4.247**
Sri Lanka	0.405	0.291	0.114	0.450	0.008	0.007	0.007	1.686**	0.083	0.063	-0.020	-3.713**
Frontier	0.561	0.171	0.389	1.596	0.007	0.007	0.007	0.335**	0.022	0.287	0.266	44.59**

Notes: '**' and '*' denotes 5% and 10% significance levels. The equality of mean and variance are tested using the two-sample t-tests and Levine test, respectively


Germany
Great Moderation
Great Austerity
Correlation
Volatility
Returns
France
Great Moderation
Great Austerity
Correlation
Volatility
Return
Italy
Great Moderation
Great Austerity
Correlation
Volatility
Return
US
Great Moderation
Great Austerity
Correlation
Volatility
Return
Canada
Great Moderation
Great Austerity
Correlation
Volatility
Return
Japan
Great Moderation
Great Austerity
Correlation
Volatility
Return
Hong Kong
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Great Austerity
Correlation
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Australia
Great Moderation
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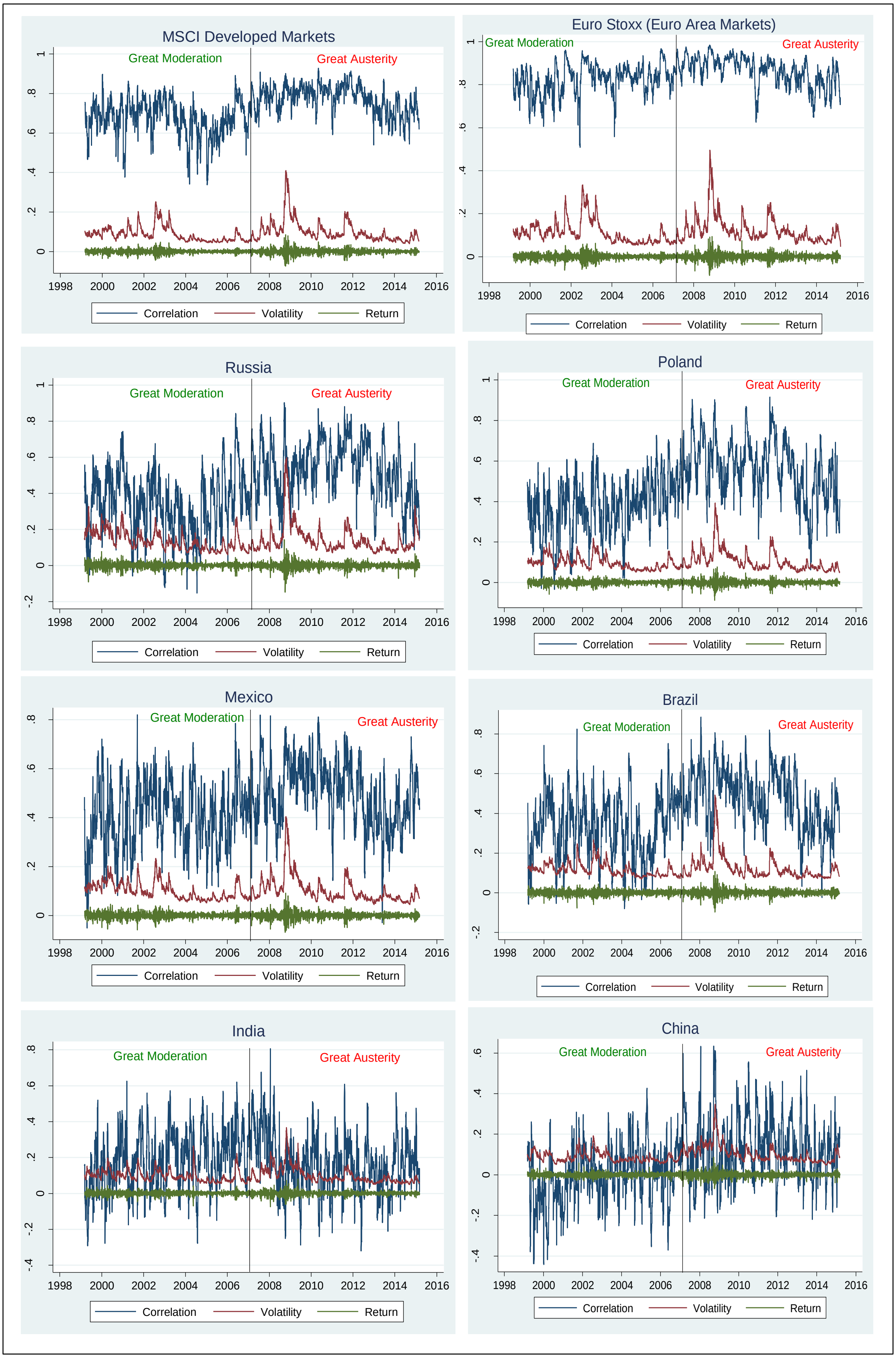
MSCI Developed Markets
Great Moderation
Great Austerity
Correlation
Volatility
Return
Euro Stoxx (Euro Area Markets)
Great Moderation
Great Austerity
Correlation
Volatility
Return
Russia
Great Moderation
Great Austerity
Correlation
Volatility
Return
Poland
Great Moderation
Great Austerity
Correlation
Volatility
Return
Mexico
Great Moderation
Great Austerity
Correlation
Volatility
Return
Brazil
Great Moderation
Great Austerity
Correlation
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India
Great Moderation
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Volatility
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China
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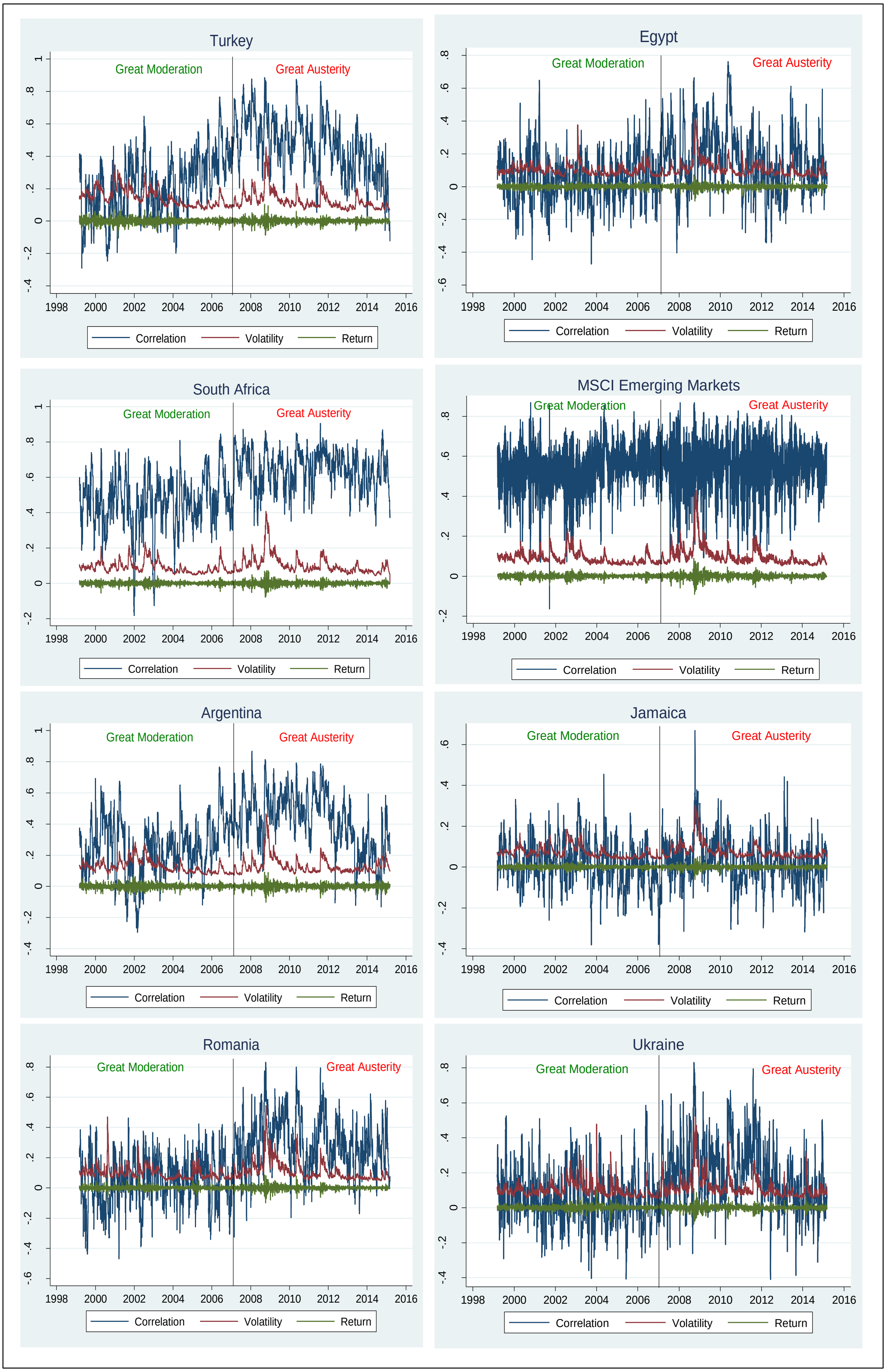
Volatility
Return


Turkey
Great Moderation
Great Austerity
Correlation
Volatility
Return
Egypt
Great Moderation
Great Austerity
Correlation
Volatility
Return
South Africa
Great Moderation
Great Austerity
Correlation
Volatility
Return
MSCI Emerging Markets
Great Moderation
Great Austerity
Correlation
Volatility
Return
Argentina
Great Moderation
Great Austerity
Correlation
Volatility
Return
Jamaica
Great Moderation
Great Austerity
Correlation
Volatility
Return
Romania
Great Moderation
Great Austerity
Correlation
Volatility
Return
Ukraine
Great Moderation
Great Austerity
Correlation
Volatility
Return
1998 2000 2002 2004 2006 2008 2010 2012 2014 2016

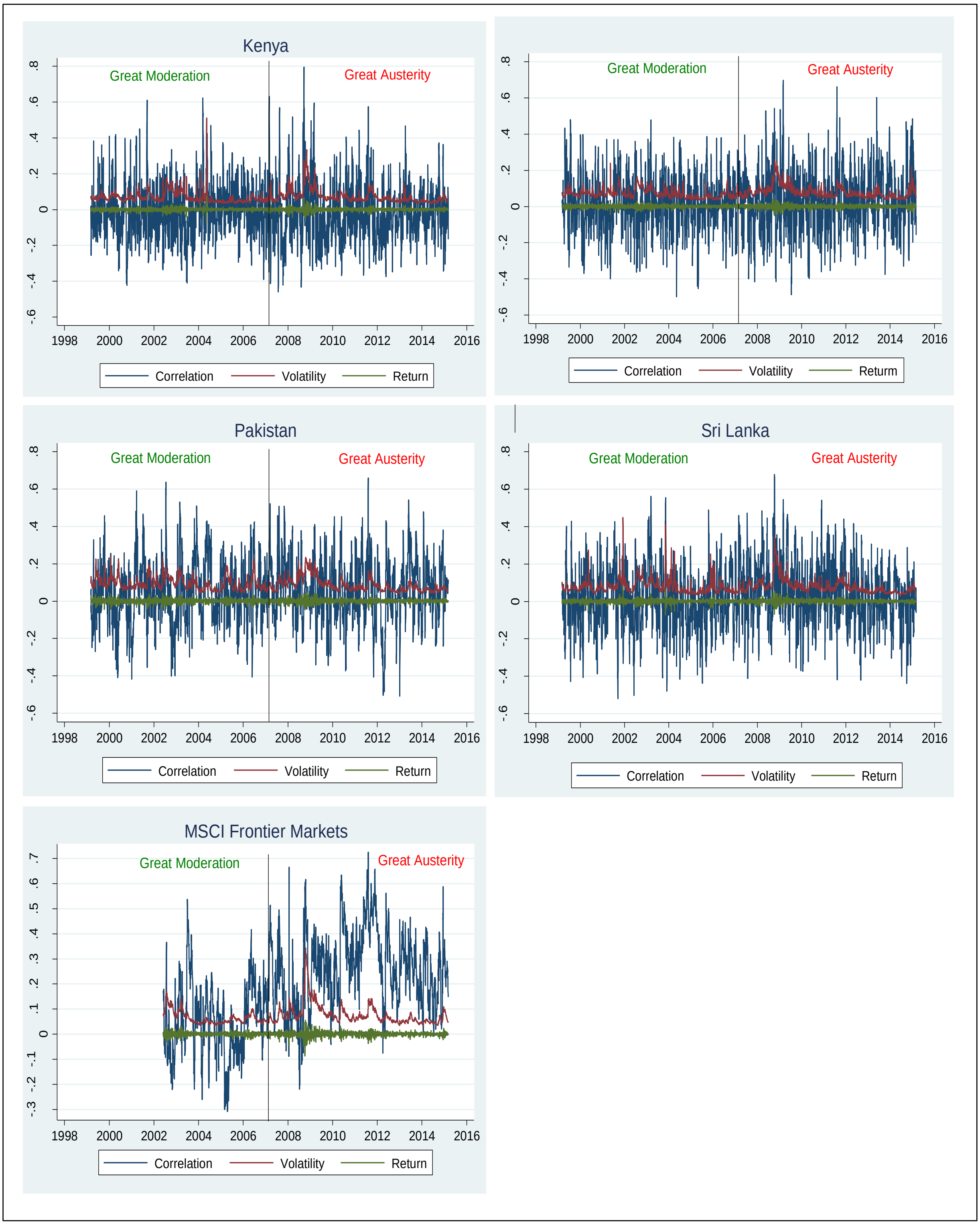


Figure 3.4: Plots of Stock Returns, Volatilities and Correlations

3.5.3 Dynamic Asset Allocation and Hedging Strategy

We set out in Table 3.7 the average values of realised portfolio weights and optimal hedge ratios for both the whole period, the GM and GA periods. Given that an accurate forecast of the covariance matrix of stock returns is crucial for optimal portfolio design and hedging strategies, the conditional variance and covariance derived from the ASY BEKK-GARCH (*1,1*) model are used to compute their average values. As earlier stated, the hedge ratios demonstrate the short position investor should take in foreign stock market to reduce the risk of a portfolio containing just domestic stock.

Starting with the GM period, the average weight for UK/Germany portfolio indicates that for a £1.00 portfolio, £0.92 should be invested in the UK market, and £0.08 should be invested in the German market. This result is similar to UK/France portfolio. It further establishes that £1.00 long position in UK market can be hedged for £0.73/£0.80 for a short position in Germany/France. The high cost of hedging suggests that the risk-adjusted performance of the resulting portfolio is less impressive. The weight for the UK/Italy portfolio indicates that £0.63 should be invested in the UK market and £0.33 should be invested in the Italian market. The hedge ratio indicates that £1.00 short position in UK market can be hedged for £0.81 for a long position in the Italian market. This poor hedging performance is also similar if UK portfolio is combined with Euro Area portfolio. Apart from German market, the portfolio weights tilted in favour holding more UK stocks than European stocks in the GA period. However, the hedge ratios have increased marginally, suggesting that hedging benefits from using these European stocks declined in turbulent period. The overall result suggests that short position in Western European stock market is less able to offset movements from a long position in UK market.

Turning to North American markets in the GM period, the average weight for the UK/US portfolio indicates that £0.50 should be invested in both UK and US markets. The hedge ratio shows that £1.00 long position in UK market can be hedged for £0.68 for a short position in the US market. This result is similar to the UK/Canada portfolio although with higher hedge ratio. In the GA period, the hedge ratio for UK/US increases while it decreases for UK/Canada portfolio. However, the UK/US portfolio offers the least-cost hedging performance, hence diversifying into North American stock markets offered stable risk-adjusted performance in both tranquil and turbulent times.

For the Asian-Pacific stock markets during the GM period, the average weight for the UK and Japan/Hong Kong/Australia portfolios indicate that £0.65/£0.64/£0.37 should be invested in the UK market and £0.35/£0.36/£0.63 should be invested in these foreign markets. Their hedge ratios show that £1.00 long position in UK market can be hedged for £0.41/£0.51/£0.58 for a short position in the Japan/Hong Kong/Australia. During the GA period, the hedge ratios decline slightly for UK/Hong Kong and UK/Australia while it increases for UK/Japan portfolio. Indeed, the UK/Japan portfolio offers the most beneficial hedging performance in the GM and GA periods.

Analysing optimal portfolio weights and hedge ratios for emerging markets in the GM period, we find that that £0.84/£0.64 should be invested in Russia/Poland and £0.16/£0.36 in UK. A £1.00 long position in the UK can be hedged for £0.39/£0.55 for a short position in Russia/Poland. The portfolio weight marginally decreases for Russian market while it increases for Polish market during the GA period. Similarly, their hedge ratios have significantly risen, suggesting decline in the hedging performance of the resulting portfolios. A UK investor holding a portfolio of these markets is worse off during the GA period as a result of the deteriorated hedging effectiveness in crisis period.

In the emerging South America during the GM period, the optimal portfolio weights indicate that £0.67/£0.82 should be invested in Mexico/Brazil while £0.31/£0.18 should be invested in UK. The portfolio holdings decline during the GA period. Also, the hedging performance for UK portfolio that includes Mexico/Brazil markets grows weaker in the GA period. For the emerging Asian markets in the GM period, the optimal portfolio weights show that £0.65/£0.59/£0.85 should be invested in India/China/Turkey and £0.35/£0.41/£0.18 in the UK market. The optimal portfolio holding of these markets did not change much in the GA period but their hedge ratios did increase significantly. The portfolio weights of UK/MSCI emerging changed significantly from holding less of UK portfolio in GM period to holding more in GA period. The hedge ratio in GA period indicates that £1.00 long position in the UK market can be hedged for £0.70 for a short position in MSCI emerging. This suggests that hedging effectiveness has deteriorated considerably in turbulent times.

On frontier stock markets, the optimal portfolio weights in GM period indicate that £0.79/£0.35 should be invested in Argentina/Jamaica and £0.21/£0.65 should be invested in UK market. The hedge ratio in GM period indicates that £1.00 long position in UK market can be hedged for £0.35/£0.35 for a short position in Argentina/Jamaica. In the GA period, the hedge ratio for Argentine market substantially increased thereby making risk-minimising investment portfolio less beneficial. The effectiveness of the hedging performance of UK portfolio that includes frontier Eastern European portfolio has increased substantially in the GA period, such that a £1.00 long position in UK market can be hedged for £0.39/£0.42 for a short position in Romania/Ukraine. Both GM and GA periods indicate more portfolio weight to UK market than

Romania/Ukraine markets. The frontier African markets in contrast show less holding of UK portfolio in both periods. The hedge ratios further show that a £1.00 long position in UK market can be hedged for a £0.34/£0.33 short position in the Nigerian/Kenyan markets. These low hedging ratios also hold for UK holdings that include Pakistan/Sri Lanka portfolio. Finally, the portfolio weights for the GM period indicate that £0.36 should be invested in the MSCI frontier markets and £0.64 should be invested in UK market. However, in the GA period the portfolio weight of UK holding reduced further in the diversified portfolio. The hedge ratio in GA period indicates that £1.00 short position in UK market can be hedged for £0.46 for a long position in MSCI frontier markets.

Figure 3.5 reports the time-varying optimal portfolio weights and hedge ratios. As a result of the time-varying correlation between UK and foreign stock indices, their portfolio weights and hedge ratios similarly exhibit substantial variability. Particularly, the wide variation in the risk-minimising hedge ratios over time suggest that portfolio managers and investors may have to rebalance their portfolios with high cost implications. The time-varying hedging ratios show substantial increase during 2001/2002 dot-com bubble bust and the 2007/2009 global financial crisis, suggesting weak hedging performance during crisis periods. This is consistent with Olson *et al.'s* (2014) findings of increased hedge ratio during extreme downturns.

Starting with UK and West European markets, the combined portfolios of UK/Germany, UK/France, UK/Italy and UK/Euro Area show that UK portfolio holding is consistently over 50% with recurrent peaks of 100% over time. The variation in UK/Italy portfolio weight is higher in the GM period but has become relatively stable in the GM period though with significant holding of UK portfolio. The UK/US portfolio weight shows significant high variation between 40% and 60%, whereas the hedging performance improves in the GA period as a result of increasing hedge ratios. A pretty interesting time-varying portfolio weight is the allocation of far less weight to UK stocks in a UK/Canada, UK/Australia and UK/MSCI developed portfolios over the GM and GA period. However, the UK/Canada portfolio offers a less effective dynamic hedging performance than UK/Australia. The time-varying plots of the UK/Japan and UK/Hong Kong portfolio weights show higher allocation to UK market than the foreign markets. Largely, the dynamic hedging ratios indicate decline in risk-minimising hedging benefits during the GA period.

Furthermore, the portfolio holding of UK/Russia, UK/Poland, UK/Brazil, UK/India, UK/China, UK/Turkey, UK/Egypt and UK/MSCI emerging markets indicates an allocation of over 50% weight to UK market in the GM and GA periods, whereas it is not clear-cut for UK/South Africa portfolio. Similarly, the portfolio mix of UK/Argentina, UK/Romania and UK/Ukraine reveals holding of over 50% of UK market in the GM and GA period, while it is not clear-cut for UK/Pakistan portfolio. Conversely, portfolio holding of UK/Jamaica, UK/Kenya, UK/Nigeria, UK/Sri Lanka and UK/MSCI frontier markets shows less than 50% of UK market in both periods. The plot of the time-varying hedging ratios suggests that a short position in the frontier markets is more able to offset movements from a long position in UK market.

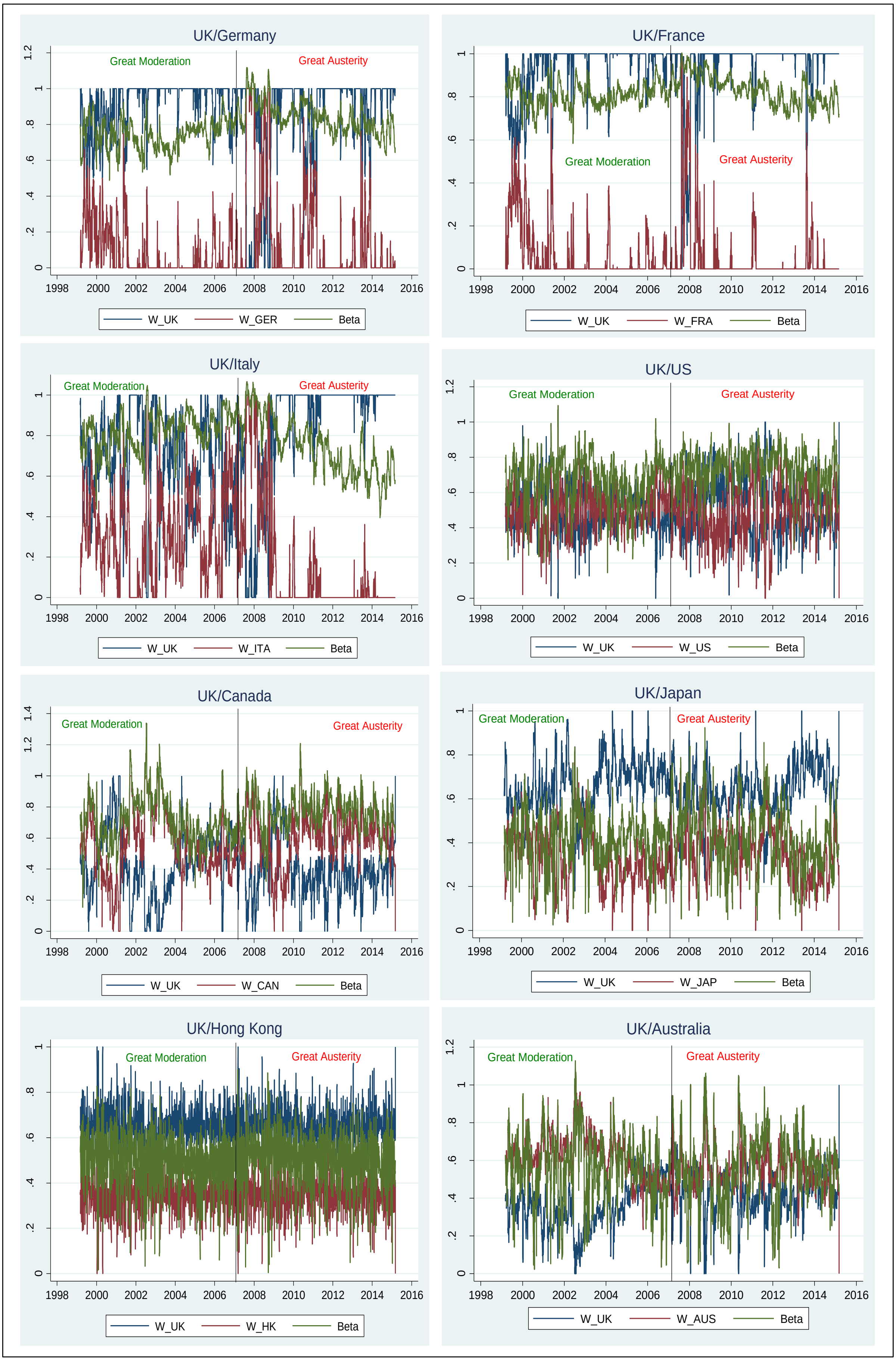
In summary, diversified portfolio holding that includes developed European markets have less variability in portfolio weights and hedge ratio, unlike the substantial variability prevalent when diversified portfolios include developed North American and Asian-Pacific markets. Indeed, the higher the variation in hedge ratio, the more costly the large and frequent adjustments to the combined portfolio. This suggests that the trading costs associated with rebalancing the portfolio will be less for UK/European portfolio than in any other foreign markets due to lower variability. The hedge ratios increased in 20 out of 29 portfolios during the GA period, suggesting that hedging performance deteriorated in non-stable times. In particular, the increase in hedge ratios in period of economic downturns (e.g. 2008 stock market crash) is an indication that foreign stock market has become less beneficial to hedge against long position in UK stock market. During crisis periods, increases in correlation and risk leads to reduction in diversification and hedging benefits.

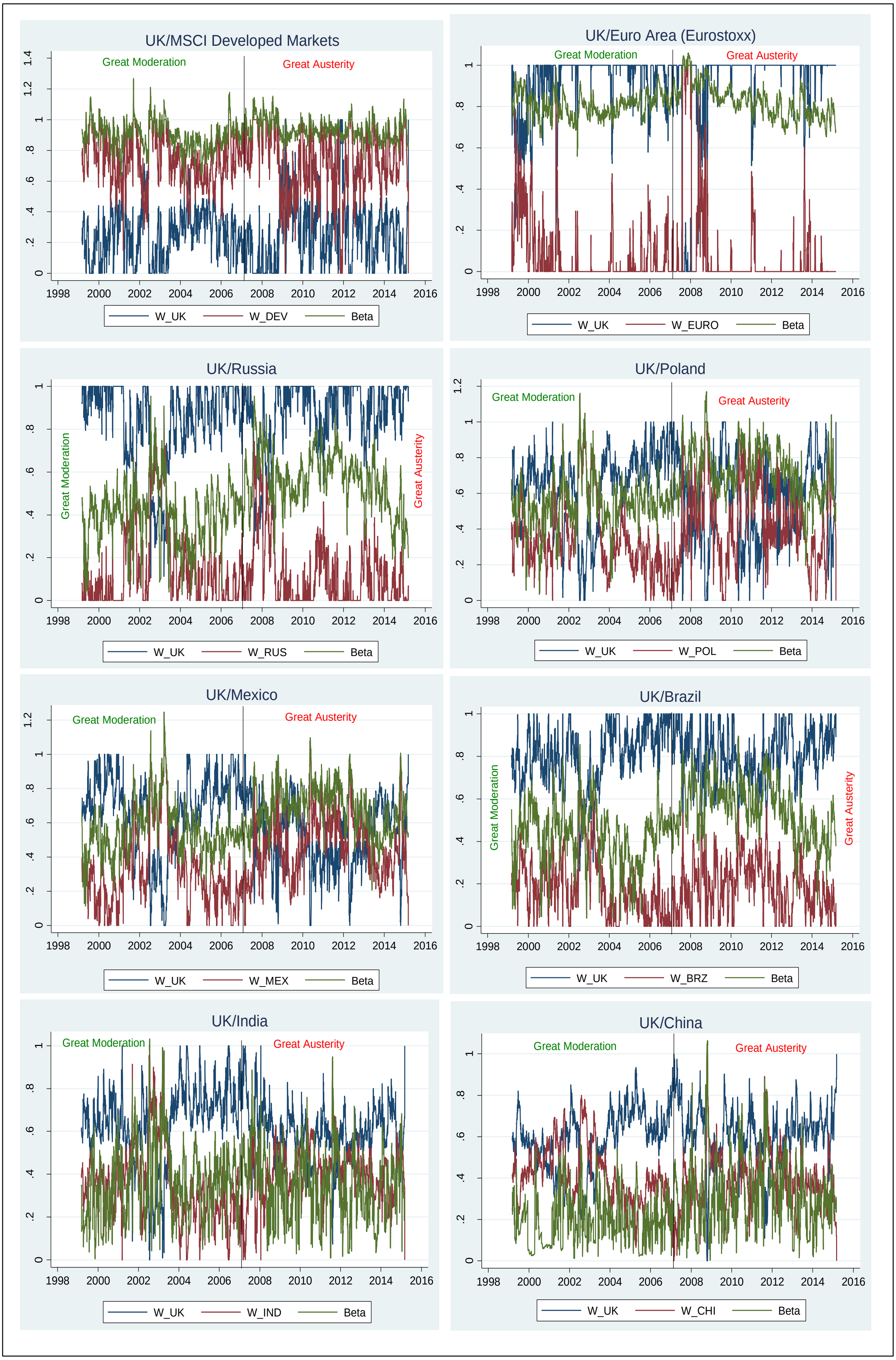
Finally, the UK investors exercise equity home bias in at least two-third of the optimal portfolio allocation, which may be attributed to asymmetric information, risk aversion and country risk. In relation to the theoretical explanations of the effect of information asymmetries, we argue that UK investors have limited information about foreign markets and may be unwilling to diversify more internationally despite the potential benefits. The results provide a rationale for equity home bias puzzle among individual and institutional investors (see Kang and Stulz, 1997, Tesar and Werner, 1995; Driessen and Laeven 2007).

Table 3.7: Average Values of Optimal Portfolio Weights and Hedge Ratios

	Great Moderation			**Great Austerity**		
Markets	W_1	W_2	β_t^{12}	W_1	W_2	β_t^{12}
Germany	0.915	0.085	0.727	0.831	0.169	0.856
France	0.935	0.065	0.802	0.947	0.053	0.865
Italy	0.673	0.327	0.807	0.847	0.153	0.863
US	0.499	0.500	0.681	0.519	0.481	0.708
Canada	0.437	0.563	0.741	0.391	0.609	0.717
Japan	0.652	0.348	0.414	0.633	0.367	0.444
Hong Kong	0.640	0.359	0.511	0.637	0.363	0.508
Australia	0.368	0.632	0.580	0.445	0.555	0.543
Developed	0.254	0.746	0.909	0.269	0.731	0.925
Euro Area	0.921	0.079	0.797	0.908	0.092	0.868
Russia	0.837	0.163	0.398	0.878	0.122	0.519
Poland	0.644	0.356	0.546	0.558	0.442	0.676
Mexico	0.674	0.326	0.582	0.524	0.576	0.629
Brazil	0.808	0.192	0.440	0.809	0.191	0.525
India	0.645	0.355	0.367	0.593	0.407	0.374
China	0.591	0.409	0.199	0.603	0.397	0.266
Turkey	0.852	0.148	0.260	0.796	0.204	0.538
Egypt	0.649	0.350	0.251	0.633	0.367	0.349
South Afr.	0.578	0.422	0.660	0.528	0.472	0.715
Emerging	0.510	0.489	0.748	0.579	0.421	0.702
Argentina	0.795	0.205	0.353	0.798	0.202	0.517
Jamaica	0.349	0.650	0.349	0.304	0.696	0.371
Romania	0.598	0.402	0.275	0.604	0.396	0.396
Ukraine	0.617	0.383	0.273	0.616	0.384	0.342
Kenya	0.373	0.627	0.326	0.343	0.657	0.325
Nigeria	0.429	0.571	0.343	0.424	0.576	0.342
Pakistan	0.604	0.397	0.296	0.491	0.509	0.292
Sri Lanka	0.445	0.555	0.336	0.384	0.616	0.370
Frontier	0.640	0.360	0.403	0.236	0.764	0.468

Notes: W_1 represents the average optimal weight of UK market; W_2 represents the average optimal weight of each foreign market; β_t^{12} represents the hedge ratio between UK and each foreign markets.


UK/Germany
Great Moderation
Great Austerity
W_UK W_GER Beta
UK/France
Great Moderation
Great Austerity
W_UK W_FRA Beta
UK/Italy
Great Moderation
Great Austerity
W_UK W_ITA Beta
UK/US
Great Moderation
Great Austerity
W_UK W_US Beta
UK/Canada
Great Moderation
Great Austerity
W_UK W_CAN Beta
UK/Japan
Great Moderation
Great Austerity
W_UK W_JAP Beta
UK/Hong Kong
Great Moderation
Great Austerity
W_UK W_HK Beta
UK/Australia
Great Moderation
Great Austerity
W_UK W_AUS Beta
1998 2000 2002 2004 2006 2008 2010 2012 2014 2016


UK/MSCI Developed Markets
Great Moderation
Great Austerity
W_UK
W_DEV
Beta
UK/Euro Area (Eurostoxx)
W_EURO
UK/Russia
W_RUS
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W_IND
UK/China
W_CHI

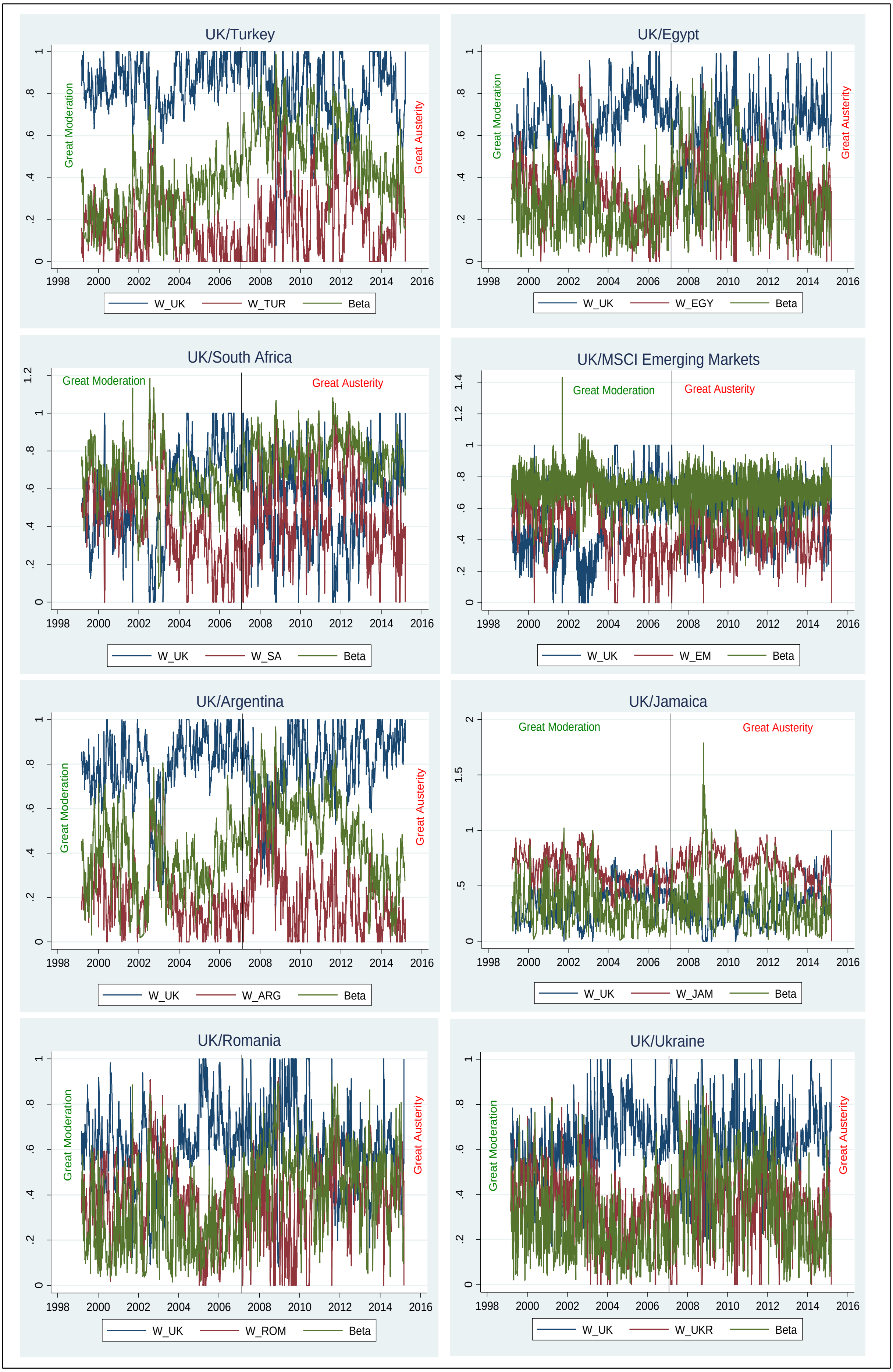
UK/Turkey
Great Moderation
Great Austerity
W_UK W_TUR Beta
UK/Egypt
Great Moderation
Great Austerity
W_UK W_EGY Beta
UK/South Africa
Great Moderation
Great Austerity
W_UK W_SA Beta
UK/MSCI Emerging Markets
Great Moderation
Great Austerity
W_UK W_EM Beta
UK/Argentina
Great Moderation
Great Austerity
W_UK W_ARG Beta
UK/Jamaica
Great Moderation
Great Austerity
W_UK W_JAM Beta
UK/Romania
Great Moderation
Great Austerity
W_UK W_ROM Beta
UK/Ukraine
Great Moderation
Great Austerity
W_UK W_UKR Beta
1998 2000 2002 2004 2006 2008 2010 2012 2014 2016

Figure 3.5: Time Varying Optimal Portfolio Weights and Hedge Ratios
Notes: the W_ denotes the weight of each portfolio in the two-asset portfolio. The Beta represents the hedging ratio, a measure of hedging effectiveness.

3.5.5 Value-at-Risk and Backtesting Analysis

Basically, portfolio returns of risky assets are exposed to market-wide variations. Indeed, an investor will be interested in evaluating and knowing the market risk level of holding a diversified portfolio of domestic and foreign stock indices. The implications of measuring market risk in portfolio management is captured by value-at-risk (VaR) metric. We therefore compare the diversification performance of the optimal risk models for the GM and GA periods using the optimal portfolio weights of Table 3.7. The use of these optimal portfolio holdings capture fat-tail and asymmetric returns that may lead to under-prediction of size and frequency of extreme market movements.[68] We similarly compare the undiversifiable UK portfolio with the diversifiable UK portfolio for the purpose of investigating the downside market risk.

We report the results of VaR estimates and backtesting procedures in Table 3.8 and Table **3.9**. Our aim is to assess the usefulness of the HS, MA, EWMA and skewed GARCH-*t* models for the one-day ahead loss predictions at 1% and 5% VaR levels for undiversified UK portfolio and each diversified portfolio. The 0.99^{th} and 0.95^{th} quantiles are predominantly used in risk management applications as well as regulatory requirements. The validity of the VaR models is then 'backtested' by comparing actual daily trading losses with the estimated VaR. The results of the backtesting procedures consist of the unconditional coverage (Kupiec test) and the conditional coverage or independence (Christoffersen test) tests. The null hypothesis of correct unconditional or conditional coverage (well specified VaR models) cannot be rejected if the empirical failure rate does not differ from the expected sequence of violations.

It is important to note that the choice of VaR model and probability level will determine the estimation of window length. However, for the purpose of making comparisons, Daníelsson (2011) argues that the estimation window should be large enough to accommodate the most stringent data criteria. Therefore, we use a sliding rolling window approach with a window size of 1000 days. This approach captures the dynamic time-varying features of the data in different time periods.[69] The use of the sliding window technique updates the estimation sample systematically by incorporating new information which become available as time elapses. According to Dimitrakopoulos *et al.* (2010), this technique takes into account implicitly

[68] The use of asymmetric BEKK GARCH-*t* model captures fat-tail distribution and asymmetric information.
[69] The use of the sliding window technique updates the estimation sample systematically by incorporating new information which become available as time elapses. For instance, the window is set between 1^{st} and 1000^{th} observations to forecast the quantiles for the 1001^{st} days. The same window is then shifted one step forward to forecast quantiles for 1002^{nd} day and so forth. This approach was adopted by Daníelsson and Moritomo, 2000; Gençay *et al*., 2003; Dimitrakopoulos *et al.,* 2010.

structural changes, such as mean and volatility shifts in the distributional properties of the understudy markets.

In the GM period, the 1% and 5% VaR thresholds of UK portfolio (i.e. undiversified portfolio) is greater than the diversified portfolio of UK/US, UK/Canada, UK/Japan, UK/Australia, UK/MSCI developed, UK/Jamaica, UK/Nigeria and UK/MSCI Frontier. In a similar vein, combining UK market with North-American markets (US/Canada) has lower estimated VaR compare to diversifying into Western Europe (Germany/France/Italy) or Asia-Pacific (Japan/Hong Kong/Australia) markets at both levels across the four models. Similarly, UK/MSCI developed portfolio has a lower downside market risk compare to UK/Euro Area portfolio. For the emerging markets, combining UK market with African emerging markets (South Africa/Egypt) has lower VaR estimates compare to diversifying into Eastern European (Russia/Poland), South American (Brazil/Mexico) and Asian Markets (India/China /Turkey). The VaR estimates are lower for combined portfolio of UK and Asian frontier markets (Sri Lanka/Pakistan) unlike the higher risk of loss for others (Argentina/Ukraine/Romania/Nigeria/Kenya). The VaR estimate for UK/MSCI frontier markets is lower than the UK/MSCI emerging markets. The VaR estimates for the MA model are the lowest for all diversified portfolios, whereas the skewed GARCH-*t* has the highest VAR estimates in 19 out of 29 diversified portfolios. The UK/China and UK/Kenya portfolios have the highest tail risk for the conditional models (EWMA and skewed GARCH-*t*), whereas the UK/Turkey and UK/Sri Lanka portfolios have the highest tail risk for the unconditional models (MA and HS). The conditional models display higher VaR estimates than the unconditional models at both levels except for UK market combined with Japan/Egypt/Romania/Sri Lanka/MSCI frontier markets. This suggests perhaps that in stable times, conditional models overestimate the level of market risk while unconditional models underestimate the level of market risk in most diversified portfolios.

By backtesting the forecasting performance in the GM period, we find that the EWMA model cannot pass the LR_{UC} and LR_{CC} tests at both significant levels for the portfolios of UK/US, UK/Japan, UK/China and UK/Romania. Based on the LR_{CC}, its average failure rate is significantly higher than the 1% VaR level in 12 out of 30 portfolios and significantly higher than the 5% VaR level in 13 out of 30 portfolios. Similarly, the skewed GARCH-*t* model cannot pass the LR_{UC} and LR_{CC} tests at both significant levels for the portfolio of UK/Germany, UK/France, UK/Euro Area (Eurostoxx), UK/Turkey, UK/Argentina, UK/Pakistan and UK/MSCI frontier markets. The insignificance of LR_{UC} and LR_{CC} tests at the 1% and 5% levels suggests that the skewed GARCH-*t* model performs very well for these diversified portfolios.

Based on the LR_{CC}, its average failure rate is significantly higher than the 1% VaR level in 6 out of 30 portfolios and significantly higher than the 5% VaR level in 12 out of 30 portfolios.

The MA and HS models reject the LR_{UC} and LR_{CC} tests at both levels for most of the diversified portfolios. They fail to reject the LR_{CC} test for the combination of UK/Germany, UK/Italy, UK/France, UK/US, UK/Japan, UK/MSCI developed, UK/Euro Area, UK/Brazil, UK/China, UK/Turkey, UK/South Africa and UK/Romania at both significant levels. However, the HS model is accepted for UK/Hong Kong and UK/Pakistan by the conditional and unconditional coverage tests at all levels. Based on the LR_{CC} for the MA model, the average failure rate is significantly higher than the 1% VaR level in 15 out of 30 portfolios and significantly higher than the 5% VaR level in 17 out of 30 portfolios. Whereas, for the HS model, the average failure rate is significantly higher than the 1% VaR level in 6 out of 30 portfolios and significantly higher than the 5% VaR level in 18 out of 30 portfolios.

In summary, the skewed GARCH-*t* model gives the best performance since its empirical failure rate is the lowest while the HS model is the least accurate because of the high failure rate recorded. We note that for the higher significant level of 5%, the effect of fat tails becomes more acute and leads to more rejections of the unconditional models than the conditional models. In fact, the underestimation of realized risk is more pronounced in the emerging and frontier equity markets than in the developed markets, whereas the tail risk of diversified portfolios is higher in the emerging markets than the developed markets and frontier markets. Overall, the EWMA VaR is very suitable for 99% confidence predictions whereas the skewed GARCH-*t* is very suitable for 95% confidence predictions, therefore suggesting that the conditional models have better forecasting performance of the downside risk of portfolio returns.

For the GA period, the 1% and 5% VaR thresholds of UK portfolio (i.e. no diversification) is greater than the diversified portfolio of UK/US, UK/Canada, UK/Hong Kong, UK/Australia, UK/MSCI developed, UK/Poland, UK/South Africa, UK/MSCI Emerging, UK/Romania, UK/Kenya, UK/Pakistan, UK/Sri Lanka and UK/MSCI Frontier. The conditional and unconditional models indicate that UK/Russia portfolio has the highest VaR estimate while UK/Kenya portfolio has the lowest VaR estimate. Similar to GM period, diversifying into Western Europe carries a higher risk of loss therefore suggesting that UK investors should consider diversifying outside developed European markets to minimise tail loss and maximise potential benefits. This conclusion is further justified by the low risk of loss generated by combining UK market with MSCI developed markets rather than diversified Euro Area markets. For the emerging markets, the lowest VaR estimates are evident in UK/India and

UK/MSCI emerging markets. For the frontier markets, the UK/Ukraine portfolio has the highest VaR estimate while UK/Kenya portfolio has the lowest VaR estimate. Overall, the unconditional models have higher VaR estimates than the conditional models.

The skewed GARCH-*t* model estimates the lowest VaR in 19 out of 29 diversified portfolios while the HS model estimates the highest VaR in 26 out of 29 diversified portfolios. The conditional models display lower VaR estimates than the unconditional models at both levels except for UK market combined with Russian/Indian/Jamaican markets. This suggests perhaps that in turbulent times, unconditional models overestimate the level of market risk while conditional models underestimate the level of market risk in most diversified portfolios.

By backtesting the forecasting performance in the GA period, we find that the EWMA model cannot pass the LR_{UC} and LR_{CC} tests at both significant levels for the UK/Mexico portfolio. It also fails to pass the LR_{UC} test at both significant levels for the UK/Nigeria portfolio but rather passed them for LR_{CC}. Based on the LR_{CC} test, its average failure rate is significantly higher than the 1% VaR level in 12 out of 30 portfolios and significantly higher than the 5% VaR level in 15 out of 30 portfolios. The skewed GARCH-*t* model cannot pass the LR_{UC} and LR_{CC} tests at both significant levels for the indices of UK/France, UK/US, UK/Canada, UK/Japan, UK/MSCI developed, UK/Euro Area, UK/Brazil and UK/Jamaica. Based on the LR_{CC}, its average failure rate is significantly higher than the 1% VaR level in 6 out of 30 portfolios and significantly higher than the 5% VaR level in 12 out of 30 portfolios. The insignificance of LR_{UC} and LR_{CC} tests at the 1% and 5% levels suggests that the skewed GARCH-*t* model performs very well in many diversified portfolios. So, skewed GARCH-*t* is the most reliable model, and it is also the least conservative as it signals lower thresholds at 1% and 5% levels.

Furthermore, the MA and HS models reject the LR_{UC} and LR_{CC} tests at 1% level for most of the diversified portfolios. Based on the LR_{CC} for the MA model, the average failure rate is significantly higher than the 1% VaR level in 9 out of 30 diversified portfolios and significantly higher than the 5% VaR level in 21 out of 30 portfolios. Whereas, for the HS models, the average failure rate is significantly higher than the 1% VaR level in 6 out of 30 portfolios and significantly higher than the 5% VaR level in 22 out of 30 portfolios. Apparently, the MA model performs better than the HS model in both tranquil and turbulent times. This is consistent with the findings of Burchi and Martelli (2016) that in periods of high volatility, the HS produces estimates of daily VaR violations.

Overall, the MA VaR is very suitable for 99% confidence predictions whereas the skewed GARCH-*t* is very suitable for 95% confidence predictions, therefore suggesting that these models have better forecasting performance of the risk of portfolio returns. The suitability of the volatility forecasting models based upon MA of historical volatility is consistent with the findings of Figlewski (1997), whereas those based upon GARCH models corroborate with the findings of So and Yu (2006), McMillan and Kambourdis (2009). The poor forecasting performance of HS method is inconsistent with the findings of Danielsson and de Vries (2000). However, the existing evidence focuses on undiversified portfolio analysis while we present evidence on internationally diversified portfolio analysis.

In summary, in both stable and crisis periods, the skewed GARCH-*t* model is the most accurate model given that it has the lowest failure rate while the HS model is the worst performing model because of its high failure rate. In terms of accuracy measures, the conditional coverage tests give more consistent results across the VaR models than the unconditional coverage tests. The 1% VaR for conditional models (skewed GARCH-t and EWMA) under-forecast market risk but performs well at 5% level, whereas the 5% VaR for conditional models (MA and HS) over-forecast market risk but performs well at 1% level. The skewed GARCH-*t* model shows superior performance for the conditional models, whereas the MA model displays better accuracy for the unconditional models for all diversified portfolios in both GM and GA periods. The forecasting performance for skewed GARCH-*t* and MA models improve during GA period, whereas they deteriorate for EWMA and HS models. Finally, most VaR estimates of the conditional models are larger than the unconditional models during the GM period while most VaR estimates of the unconditional models are higher than the conditional models during the GA period. This suggests that conditional models predict higher tail risk during tranquil times whereas the unconditional models predict higher tail risk during volatile period.

Table 3.8: VaR Analysis during the Great Moderation Period

Markets		EWMA			Skewed GARCH-*t*			Moving average			Historical simulation		
		VaR	**LR_{UC}**	**LR_{CC}**	**VaR**	**LR_{UC}**	**LR_{CC}**	**VaR**	**LR_{UC}**	**LR_{CC}**	**VaR**	**LR_{UC}**	**LR_{CC}**
UK	1%	19.81	XXX	X	20.57			16.07		XX	19.19	XXX	
	5%	14.01			14.54			11.36	XXX		11.08	XXX	
Ger.	1%	20.05	XX		20.63			16.34		XX	19.58	XXX	
	5%	14.17			14.59			11.55	XXX		11.56	XXX	XXX
Fra.	1%	19.99	XX		20.59			16.19		XX	19.29	XXX	
	5%	14.04			14.56			11.45	XXX		11.49	XXX	
Ita.	1%	19.87	XXX		20.38	XX		15.80		XX	19.62	XXX	
	5%	14.05			14.41			11.17	XXX		11.22	XXX	
US	1%	18.12			17.48			13.52	XX		16.11	XXX	
	5%	12.81			12.36	XX		9.586	XXX		8.756	XXX	
Can	1%	17.47	XX		18.07			13.27			15.33	XXX	
	5%	12.35		XX	12.78	X	XX	9.556	XXX	X	9.669	XXX	XX
Jap.	1%	18.76			18.15		X	15.82	XXX		19.59	XXX	
	5%	13.26			12.83			11.18	XXX		11.26	XXX	
HK	1%	20.14	XXX	XXX	19.31	XX	XXX	14.59		X	18.95	XXX	XXX
	5%	14.24			13.65			10.32	XXX	XXX	10.14	XXX	XX
Aus.	1%	18.44	XXX	XX	18.68	XX	XX	12.15		XXX	16.02	XX	
	5%	13.04			13.21		XX	8.589	XX	XXX	8.598	XX	XXX
Dev.	1%	17.41			17.49			13.33			15.25	XXX	
	5%	12.31		XX	12.36	XX	XXX	9.429	XXX		9.288	XXX	
Euro	1%	19.89	XXX	X	20.62			16.23		XX	19.34	XXX	
	5%	14.06			14.58			11.57	XXX		14.58	XXX	
Rus.	1%	21.72	XXX	X	23.66			16.93		XX	20.94	XX	
	5%	15.36		X	17.21		XX	11.79	XXX	XX	11.02	XXX	XX
Pol.	1%	23.45	XXX		22.39	XX		16.32			20.45	XXX	
	5%	16.58			15.83			11.58	XXX	X	10.63	XXX	X
Mex	1%	22.14	XX	XX	23.21			16.29			19.37	XXX	
	5%	15.41			15.90	XX	X	11.52	XXX		10.52	XXX	XX
Bra.	1%	21.61	XX		22.46			16.69			20.57	XXX	
	5%	15.28			15.88	XXX		11.81	XXX		11.06	XXX	
Ind.	1%	21.78	XXX	XXX	25.06	XX	XXX	17.70		XXX	21.93	XX	
	5%	15.41		X	17.31		XX	12.68	XX	XXX	12.21	XX	XXX
Chn.	1%	34.26			29.00			16.08			17.42		
	5%	24.22			20.51	XX		11.37	XXX		10.54	XXX	
Tur.	1%	22.38	XX	X	23.35			16.70		X	21.48	XXX	
	5%	15.83			16.51			11.81	XXX	X	11.78	XXX	XX
Egy	1%	19.22			21.26			17.57			21.65		XX
	5%	13.59		XXX	15.04	XX	XXX	12.42	XXX	XX	11.26	XXX	XXX
SA	1%	21.45	XX		23.47			17.04			20.82	XX	
	5%	15.16			16.59	X		12.05	XXX	XX	10.63	XXX	X
EM	1%	21.55	XXX		22.83	X	XX	16.27		XXX	20.31		
	5%	15.24		XXX	16.14		XX	11.51	XXX	XXX	11.41	XXX	XXX
Arg.	1%	24.06	XX		26.49			17.66			21.99	XX	
	5%	17.01		X	18.73			12.49	XXX	X	12.25	XXX	X
Jam.	1%	18.86	XX		19.11			13.15			14.66		X
	5%	13.33		XX	13.51	XX		9.296	X		7.960	X	
Rom	1%	18.98			20.44			17.22			20.84	XXX	
	5%	13.42			14.45	X	X	12.17	XXX	X	10.73	XXX	
Ukr	1%	29.97	X		37.33			20.86			26.19		
	5%	21.19		XX	26.39	XXX		14.75	XXX	X	11.59	XXX	X
Ken	1%	24.53		XXX	37.59		X	17.42		XXX	18.34		XXX
	5%	17.34	XXX	XXX	26.58	XXX	XXX	12.32	XXX	XXX	7.857	XX	XXX
Nig.	1%	19.13		XXX	17.73	XX		14.26		XXX	16.39		XXX
	5%	13.53		XX	12.53	X	X	10.08	XXX	XXX	9.064	XX	XXX
Pak.	1%	17.25	XX	XX	21.84			18.19		XX	21.22	XX	XXX
	5%	12.19	XX	XXX	15.44			12.86		XXX	13.90	XX	XXX
Sri	1%	13.69	XX	XX	22.56			20.21		XXX	28.37		XXX
	5%	9.683	XXX	XXX	15.95	XXX	XX	14.29	XXX	XXX	11.27	XXX	XXX
FM	1%	13.67	X		14.06			12.67	XX		15.79		
	5%	9.665			9.941			8.957	X		8.647	X	

Notes: This table summarises the VaR estimates and the Kupiec unconditional (LR_{UC}) and Christofferson conditional (LR_{CC}) coverage tests for undiversified and diversified UK portfolios in the GM period. The 'XXX', 'XX' and 'X' denote that the respective models have passed the likelihood ratio backtesting tests statistics at the 1%, 5% and 10% significant levels for the conditional and unconditional coverage tests.

Table 3.9: VaR Analysis during the Great Austerity Period

Markets		EWMA			Skewed GARCH-*t*			Moving average			Historical simulation		
		VaR	LR_{UC}	LR_{CC}	VaR	LR_{UC}	LR_{CC}	VaR	LR_{UC}	LR_{CC}	VaR	LR_{UC}	LR_{CC}
UK	1%	14.65	XXX	XX	12.74			21.96			27.47	XXX	
	5%	10.36	XXX	XXX	9.007			15.53	XXX	XXX	15.76	XXX	XXX
Ger.	1%	14.62	XX		13.07			22.39			27.55	XXX	
	5%	10.33	XX		9.241		X	15.83	XXX	XXX	15.86	XXX	XXX
Fra.	1%	15.29	XXX		13.69			23.54			29.13	XXX	
	5%	10.81	XX	XX	9.678			16.65	XXX	XX	16.92	XXX	XX
Ita.	1%	15.92	XXX		14.48			23.55			29.76	XXX	
	5%	11.26	XX	XX	10.23			16.64	XXX		17.37	XXX	XX
US	1%	12.14	XXX		10.87			20.15			24.88	XXX	
	5%	8.582	XXX		7.684			14.24	XXX		14.35	XXX	
Can.	1%	12.41	XXX	XX	10.25			18.18			22.69	XXX	
	5%	8.774	XX		7.245			12.86	XXX		13.54	XXX	
Jap.	1%	13.53	XX		14.67			21.26		X	26.59		
	5%	9.563			10.37			15.03	XXX	XX	15.47	XXX	X
HK	1%	12.44	XXX	XXX	11.55	XXX	XXX	19.89	XX		23.86	XXX	
	5%	8.798			8.167		XX	14.07	XXX	XX	15.53	XXX	XXX
Aus.	1%	12.52	XXX		12.01	XX		17.56		XX	23.33	XXX	
	5%	8.851			8.492		X	12.41	XXX	XXX	12.50	XXX	XXX
Dev.	1%	11.92	XXX		10.69			20.24	XX		26.74	XXX	
	5%	8.429	XXX		7.559			14.31	XXX	X	14.99	XXX	XX
Euro	1%	18.82	XXX		17.83			26.95			33.76	XXX	
	5%	13.30			12.60			19.06	XXX	XXX	20.15	XXX	XXX
Rus.	1%	58.31	XXX		55.67	XXX		41.77		X	46.92	XX	XX
	5%	41.25	XXX		39.36			29.53	X	XXX	29.27	XX	XXX
Pol.	1%	13.64	XXX	XX	12.66	XX		21.34			26.56	XXX	
	5%	9.642	XXX	XXX	8.951		XX	15.09	XXX	XXX	15.11	XXX	XXX
Mex	1%	16.05	XXX		15.05			19.23			21.72	XXX	
	5%	11.34			10.63		XX	13.59	XXX		12.83	XXX	XXX
Bra.	1%	15.52	XXX		13.88			22.07			24.83	XXX	
	5%	10.98	XXX		9.812			15.61	XXX	XX	15.38	XXX	XX
Ind.	1%	21.79	XXX	XXX	24.48	XX	XXX	17.93		XXX	21.94	XX	
	5%	8.653		XXX	8.841		XXX	12.19	XXX	XXX	11.67	XXX	XXX
Chn	1%	19.18	XXX		17.75	X		18.37			23.55	XX	
	5%	13.56			12.55			12.99	XXX		12.98	XXX	
Tur.	1%	14.61	XXX		16.19	XX	XX	23.08		X	31.21	XX	
	5%	10.33	X	X	11.45			16.32	XXX	X	16.22	XXX	XX
Egy	1%	16.99	XXX	XX	18.81			23.28			28.12	XX	
	5%	12.02		XXX	13.30		X	16.46	XXX	XXX	16.74	XXX	XXX
SA	1%	13.16	XXX	XX	11.31	XX		19.98			25.16	XX	
	5%	9.307	XX	X	7.997			14.13	XXX		14.81	XXX	
EM	1%	13.78	XXX	X	12.17	XX	XX	21.31			26.67	XXX	
	5%	9.744	XX	XXX	8.604			15.07	XXX	XXX	15.14	XXX	XX
Arg	1%	14.65	XXX		13.48			22.01		X	27.24	XXX	
	5%	10.36	XXX	XXX	9.536		X	15.56	XXX	XXX	15.95	XXX	XXX
Jam	1%	14.66	XX		14.49			12.43			14.16		
	5%	10.37			10.25			8.786			9.011		
Rom	1%	11.90	XXX	XXX	11.16	X		19.43			23.88	XXX	XXX
	5%	8.414		X	7.887			13.74	XX	XXX	13.93	XXX	
Ukr	1%	16.34	XXX	XXX	16.07			21.61		XXX	32.78	XXX	XXX
	5%	11.55	XXX	XXX	11.37		XX	15.28	XXX	XXX	14.79	XXX	
Ken	1%	8.238			8.233			11.73	XX		13.20	XXX	
	5%	5.825		XX	5.821	XX	X	8.295	XXX		8.162	XXX	X
Nig	1%	19.36	XX	XXX	15.99		XXX	15.96		XXX	20.58		XXX
	5%	13.69		XXX	11.03	X	XXX	11.28	XX	XXX	11.77	XXX	XXX
Pak.	1%	10.18	XX	XXX	11.20		XX	15.09			17.18		
	5%	7.198			7.919			10.67	XXX		9.921	XXX	XX
SL	1%	11.39			11.74			13.53		XX	16.07	XXX	
	5%	8.052		XXX	8.298	XX	X	9.566	XXX	XXX	10.08	XXX	XX
FM	1%	10.89	XXX		9.943	XXX		12.57			16.06	XXX	XXX
	5%	7.770		XXX	7.031			8.891	XXX	XXX	8.960	XXX	

Notes: The notations in this table are similar to notes provided in Tables 3.8.

3.6 Conclusions

We study portfolio management by: (1) examining nature of spillover effects and time-varying conditional correlation using asymmetric BEKK-GARCH model (2) constructing optimal dynamic portfolio weights and hedge ratios (3) using optimal portfolio weights to analyse the VaR of diversified portfolios. By splitting the period 1999 – 2015 into Great Moderation (GM) and Great Austerity (GA), our contributions have shed light on strategic portfolio management of UK securities combined with a large cohort of developed, emerging and frontier economies.

Firstly, the empirical estimates indicate that the levels of shock and volatility transmissions have increased in the GA period, implying that the markets have become more integrated in recent years. The cross-market asymmetric responses are stronger particularly between the UK and developed markets. This suggests that the asymmetric spillovers maybe due to asymmetries in market size such that frontier/emerging markets are significantly smaller than developed markets. The transmission of shocks from the UK economy toward frontier and emerging markets are stronger in the GA period, and become less marked during the GM period. We conclude that the spillover of shocks and volatilities from frontier and emerging markets perhaps reflect adverse effects of internal and external crises on these markets, which in turn, influence the UK market due to negative impact on factors such as UK exports and withdrawal of foreign portfolio investments from the UK (see Samarakoon, 2011). This evidence reinforces the existing evidence on transmission of shocks and volatilities in global financial markets.

The time-varying conditional correlation between UK and these markets in the GA period is higher than GM, which may undermine the potential risk-return benefits indicated by international diversification strategies. However, the less than perfect integration of international stock markets can still create opportunities for international diversification. Unequivocally, the extent of market interdependence has great implication for international investors and domestic economies when shocks are being transmitted. The correlation between UK and frontier markets is generally weak in GM and GA periods, therefore including frontier markets in the investment portfolio allocation may increase benefit from risk-return trade off. This result corroborates with the findings of Caporale *et al.* (2006), suggesting that international diversification is effective in reducing portfolio risk in pre-crisis period, that is, GM period in our study. As a result of increasing integration of international stock markets, financial market operators will seek alternative more refined strategies to isolate from macroeconomic risks. An alternative strategy is to achieve optimal risk hedging benefits by taking an appropriate position on the foreign stock markets.

We consider the possibility of constructing an optimal portfolio allocation and risk-minimising hedging strategies. Our results confirm the existence of equity home bias due to over 50% allocation to UK assets in at least two-third of the diversified portfolio holdings under consideration. This is an indication that increasing integration induces more holding of domestic asset than foreign asset in portfolio allocation decisions. However, UK investors do allocate their foreign holdings towards markets, especially frontier markets, which provide greater diversification benefits. In another case, the dynamic hedge ratios show that foreign stock markets in developed and emerging countries provide sound hedging instrument for UK market, particularly in GA period. The hedge ratios of these portfolios significantly increased from GM to GA period in 22 out of 29 stock markets, suggesting deterioration in hedging benefits. We conclude that the cheapest hedge is to long UK portfolio and short Chinese portfolio, whereas most expensive hedge is to long UK portfolio and short MSCI developed portfolio. These results support evidence of equity home bias though with an effective hedge against domestic asset (see Coeurdacier and Guibaud, 2011).

For the VaR analysis, we find that the combination of UK portfolio with markets in North America/Africa/Asia reduces risk of investment loss much more than diversifying into European markets. Particularly, American markets provide diversification opportunities than European markets. Except for Italy and Russia, the risk of investment loss diminishes in all diversified portfolio during the GA period. We conjecture that the quantitative easing policies and the fiscal stimulus measures of the developed economies implemented to mitigate the recent series of economic downturns have boosted market liquidity and reduced market risk to a large extent.

Furthermore, the skewed GARCH-*t* VaR model performs well in estimating market risk at 5% level during GM and GA periods, whereas the MA model shows superior performance at 1% VaR level across a large cohort of diversified portfolios. We argue that portfolio managers should consider using the GARCH models to provide accurate forecasting of market risk of international portfolio diversification because they capture the inherent time-dependency within volatility. Overall, accurate forecast of VaR will guide investors' decision making on international portfolio investment and skewed GARCH-*t* performs well in estimating market risk during GM and GA periods. This suggests that tail behaviour should not be ignored in proper assessment of market risk especially in turbulent periods. As the evidence shows deterioration in the performance of VaR models during GA period, portfolio managers should take special caution in estimating VaR by using appropriate backtesting procedures in turbulent times.

We conclude that international investors would benefit from portfolio diversification based on optimal asset allocation and robust risk management analysis. Relative to developed and emerging markets, portfolio diversification that includes frontier markets does provide effective hedge against UK stock market and reduce risk of investment loss in both GM and GA periods. The implications of these results are important for different types of operators. For speculators, higher stock market integration during GA period reduces diversification benefits when they are most required. For hedgers, the usefulness of the foreign stock index to hedge UK stock index diminishes significantly during GA period. Therefore, UK investors should rebalance their investment portfolio optimally and use foreign equity index as a good hedging instruments against adverse shifts in the investment opportunity set given the changing economic conditions of the economy. Finally, portfolio managers, financial analysts and investors should actively and effectively manage their portfolio investment based on long-run persistence, shock and volatility transmissions, correlation dynamics, optimal portfolio design, hedging effectiveness and downside market risk.

Research Conclusions

This thesis explores the dynamics of market efficiency, market integration, portfolio diversification and risk management of developed, emerging and frontier equity markets. Our findings demonstrate several important implications in the evolution of stock market integration, forecasting future volatility, dynamic asset allocations and hedging strategies as well as downside risk management between UK and a large cohort of stock markets. We have indicated in this study that market efficiency, market integration, portfolio allocation and risk-minimising hedging strategies are changing overtime and across markets.

Firstly, the evidence of time-varying return predictability, particularly in emerging and frontier markets is consistent with the adaptive market hypothesis (AMH). Indeed, the degree of market efficiency deteriorates rapidly during turbulent times (that is, market anomalies such as market manias, panics and crashes) for most markets. Hence, the application of short-horizon technical trading rules could potentially exploit profit opportunities inherent in these markets. However, the risk-adjusted profits that can be earned in the emerging and frontier markets are economically small even before transactions costs are accounted for. On the basis of dynamic profitability, technical trading rules that account for changing market conditions tend to beat the buy-and-hold strategy in at least half of the understudy markets both in stable and crisis periods. Moreover, macroeconomic fundamentals and changing market conditions have been found to be key determinants of technical trading rules profitability, which is in line with AMH. We conclude that financial market operators should take into account both fundamental and non-fundamental impacts on stock prices movements in the assessment of the trading rule profitability.

Secondly, the evidence shows that the financial linkages (that is, shock and volatility spillovers) between UK and US markets have become stronger since the establishment of the European Monetary Union. As a matter of fact, the degree of macroeconomic convergence, similar stock market characteristics and financial contagion are propelling stock market integration between UK and US. However, we argue that the inconsistency between macroeconomic policies and financial stability in the periods of Second World War and Bretton Woods system caused a decline in stock market integration, while the increasing integration in subsequent periods has been driven primarily by converging macroeconomic fundamentals, financial liberalisation, as well as market contagion. As a consequence, policymakers should take these drivers into account in appropriately calibrating their policy response.

Thirdly, we have also established shock and volatility spillover effects are strongest between UK and developed markets and weakest between UK and frontier markets. This suggests that strong financial linkages could increase the vulnerabilities of domestic markets to any global shocks and reduce benefit of international diversification, whereas weak market linkages could insulate domestic markets from international shocks and increase diversification benefits. In fact, we find that in most cases markets (e.g. developed markets) with higher efficiency, also exhibit stronger integration. It is also evident that stock market integration rises generally in crisis period, which suggests some form of market contagion. However, if integration continues to increase with developed markets then it will further diminish potential portfolio diversification benefits. Nevertheless, the diminished portfolio diversification benefits arising from higher efficient and integrated markets will motivate international investors to look for new investment opportunities in emerging and frontier markets for the purpose of improving international diversification benefits.

Seemingly, there is an improvement in reward-to-risk performance when assets from emerging and frontier markets are added to a benchmark UK stock market. Although, there is a high level of equity home bias associated with a UK investor, which may be ascribed to factors such as role of asymmetric information, risk aversion and country risk. Depending on the risk management strategies of investors, increasing stock market integration may lead to decline/increase of investment loss whether in stable or crisis periods. However, a UK investor will be better off holding portfolio that consist of frontier markets because of lesser integration, lower cost of hedging strategy and minimal investment loss. More interestingly for investors and portfolio managers, the volatility models are especially useful in forecasting market risk exposure for synthetic portfolios of domestic and foreign stocks.

It is important to highlight the major limitations and identify the areas of further research for each chapter. The major limitation observed in chapter one is the unavailability of macroeconomic and financial data for the frontier markets to broaden the analysis of the drivers of technical trading rules profitability. However, the first chapter can be further extended by using rolling window analysis based on high frequency financial data to explain the time variation in market efficiency. Also, the determinants of technical trading rules profitability may be examined in each market category (that is, developed, emerging and frontier markets) in order to ascertain how macroeconomic fundamentals and changing market conditions are consistent with AMH. Similarly, further studies are required on investigating how temporary market inefficiencies, risk premiums, market microstructure deficiencies and other factors can influence technical trading rule profitability.

The major limitation of the second chapter is the unavailability and inaccessibility of 8 decades long data for market capitalisation, trade, stock turnover and other financial data that could be potential drivers of UK and US stock market integration. Further research could explore new macroeconomic data and use the mixed data sampling regression to predict or forecast the integration between US and UK financial markets. Likewise, further research on volatility impulse response functions may consider the impact of asymmetries in the transition of historical volatility shocks.

A crucial limitation in chapter three is the unavailability of econometric models that can examine time variation in shocks and volatility spillovers given the changing economic conditions. In essence, future research could focus on developing models that capture the time-varying spillover effects across financial markets. Similarly, examining the change in Sharpe ratio, dynamic tail risk and time-varying hedging effectiveness are potential areas to consider in future research. This will improve our knowledge of market contagion, volatility forecasting, hedging strategies and tail risk analysis.

In conclusion, our empirical findings have various important policy implications that is germane to risk managers, portfolio managers, institutional investors, policy-makers and researchers. Given the time variation in market efficiency, market integration, portfolio allocation and hedging effectiveness, financial market operators will optimise portfolio diversification benefits through active portfolio management strategies by taking into account changing macroeconomic fundamentals and economic conditions. Fundamentally, the possibility of exploiting profit opportunities in emerging and frontier markets suggests that diversifying into these markets will yield potential benefits for investors in developed markets. On a final note, policymakers should carefully review the regulatory framework and implement macroeconomic policies that will mitigate threat of financial contagion, improve market liquidity and promote overall financial stability from the standpoint of adaptive market hypothesis instead of over-reliance on efficient market hypothesis.

Data Appendix: Macro and Financial Data

	Macro/Financial Data	Description	Source
1.	<u>Short-Term Rates</u> Discount rate on Treasury bills (07/1939 – 12/1954) for UK 3-month Treasury Securities for the UK (01/1955 – 03/2015) 3-month Treasury Bill for the US (01/1935 – 05/2015)	Monthly yield and not seasonally adjusted Monthly yield and not seasonally adjusted Monthly yield and not seasonally adjusted	Capie and Webber (1985) OECD Board of Governors of the Federal Reserve System
2.	<u>Long-Term Rates</u> Long-term government bond yields for the UK (1935 – 1959) Long-term government bond yields (10 year) for the UK (01/1960 – 03/2015) Long-term government bond yields for the US (10/1941 – 12/1954) Long-term government bond yields for the US (01/1955 – 03/2015)	Monthly yield and not seasonally adjusted Yearly yield and not seasonally adjusted Monthly yield and not seasonally adjusted Monthly yield and not seasonally adjusted	Source: Janssen *et al.* (2002), Mitchell (1988). OECD NBER OECD
3.	Industrial production for the UK (1948 – 1955) Industrial Production Index for the UK (01/1956 – 02/2015) Industrial Production Index for the US (07/1935 – 05/2015)	Monthly index and seasonally adjusted Yearly index and seasonally adjusted Monthly index and seasonally adjusted	OECD ONS Board of Governors of the Federal Reserve System
4.	<u>Inflation</u> Wholesale price index, all commodities for Great Britain (07/1935 – 12/1954) Consumer price index of all items in the UK (01/1955 – 03/2015) Wholesale price index, all commodities for Great Britain (07/1935 – 12/1954) Consumer price index of all items in the US (01/1955 – 03/2015)	Monthly index and not seasonally adjusted Monthly index and not seasonally adjusted Monthly index and seasonally adjusted Monthly index and not seasonally adjusted	NBER OECD NBER OECD
5.	US/UK Foreign Exchange rate (07/1935 – 06/2015)	Monthly series and not seasonally adjusted	Board of Governors of the Federal Reserve System
6.	US average oil price (1935 – 1945)	Yearly series and not seasonally adjusted	BP Statistical Review of World Energy Dow Jones Company

	Spot oil price: West Texas Intermediate (01/1946 – 07/2015)	Monthly series and not seasonally adjusted	
7.	Historical gold prices (1935 – 1967) Gold Fixing Price (04/1968 – 06/2015)	Yearly series and not seasonally adjusted Monthly series and not seasonally adjusted	www.nma.org/pdf/gold/his _gold_prices.pdf London Bullion Market Association
8.	Reference dates for the UK business cycle (07/1935 – 05/1955) OECD based recession indicators for the UK from the peak through the trough (09/1955 – 06/2014) NBER based recession for the US from the peak through the trough (07/1935 – 09/2014)	Monthly series and not seasonally adjusted Monthly series and not seasonally adjusted Monthly series and not seasonally adjusted	Friedman and Schwartz (1982) Federal Reserve Bank of St. Louis Federal Reserve Bank of St. Louis

Notes: OECD – Organisation for Economic Cooperation and Development; NBER - National Bureau of Economic Research; ONS – Office of National Statistics. A value of 1 is a recessionary period, while a value of 0 is an expansionary period.

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