

Impact of News Announcements on Stock Market Returns and Volatility

Spillover Across North America, European Union and Pacific Asia

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A Thesis

Presented to

The Faculty of Business Administration and Economics

at Notre Dame University-Louaize

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In Partial Fulfillment

of the Requirements for the Degree

Master of Science

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by

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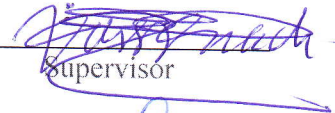
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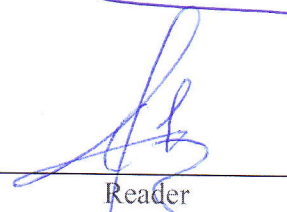
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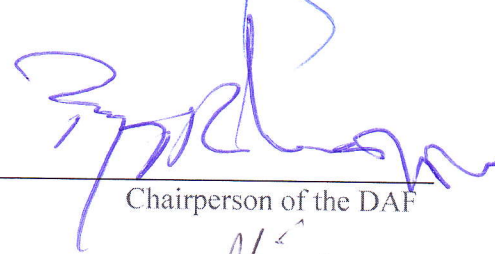
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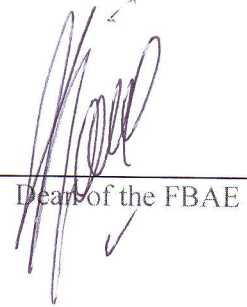
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## ABSTRACT

**Purpose** – This thesis has two objectives. The first one is to test empirically the level of interdependence across major stock markets returns, namely, US, EU, and Asia in terms of return and volatility spillover. The second one is to evaluate the impact of news announcements on their stock market volatility.

**Design/methodology/approach** – To model the volatility of the three above mentioned stock markets we apply a battery of univariate time series models from the GARCH family. Dickey Fuller unit root test is used in order to ensure that the three return series are stationary. The mean equation in the GARCH is assumed to follow an ARMA process and the residuals of the GARCH are tested for heteroscedasticity and autocorrelation using the Ljung-Box test. A comparative approach is considered and the best GARCH model is the one that has homoscedastic and not autocorrelated errors. To test for volatility spillover we consider a simultaneous equation model estimated using a three stage least square approach that tackles the problem of endogeneity. To sum up, this study applies a combination of econometric tools – ARMA-EGARCH and 3SLS technique to spot both the instantaneous and delayed volatility spillovers among major stock market returns and to examine the impact of news surprises.

**Findings** – Empirical results show that news announcements significantly affect stock market returns in US and Asia. Furthermore, news announcements affect the transmission of volatility between US and Asian stock markets, however; no volatility spillover was found between EU and US in terms of news announcements. We also found significant evidence of bidirectional volatility transmission between US and Asia stock market returns and between EU and Asia stock market returns. Furthermore, Negative shocks are found to have more impact on all stock returns under study than positive shocks.

**Practical implications** – Our empirical findings contribute to the literature of interdependence among major stock markets returns. It provides insight on the impact of news announcements on stock market returns and volatility spillover. It also provides guidance for investors and portfolio managers to effectively implement diversification and hedging strategies.

**Originality/value** – Most studies consider economic surveys such as the consumer price index, the targeted federal funds rate, the unemployment rate, and non-farm payroll to capture the effect news announcements on volatility spillover. This thesis uses a one comprehensive indicator for news announcements, the Bloomberg Economic Surprise Index (BESI). BESI encompasses all the above and takes into consideration changes in 39 macroeconomic and financial indicators. Second, this thesis employs comprehensive data covering recent period and includes major stock markets around the world, namely, US, EU, and Pacific Asia countries.

**Keywords** – Volatility, Macroeconomic news announcements, Surprise shock, US, EU, Asia, EGARCH, Spillover, and Three-stage least square.

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## **Chapter 1**

### **Introduction**

#### **1.1 Background**

Markets across the world experience a growing foreign presence. The structure of interdependence among financial markets has long been questioned. In any market, the investor's main concern revolves around maximizing profits while reducing risk (Levy & Sarnat, 1970). This is achieved through the distribution of funds among different assets, in other words through diversification. The theory of diversification was established many decades ago among weakly correlated stocks in a single market, and later extended to include different asset classes of a single market (Rezayat & Yavas, 2006b). Ultimately, this theory was extended to include different asset classes along several markets, a concept more commonly known as international portfolio diversification (Byers & Peel, 1993). Surz (2018), claims that about 20 percent of US nonfinancial shares were held by overseas investors in 2015 matched to about 10 percent in 2000. The same trend is observed in the UK (54% foreign ownership in 2017), in Germany (64%) and Japan (32%). Indeed, foreign presence in equity markets increased stock market co-movement and financial integration that resulted in volatility spillover between market returns (Surz, 2018). However, there is evidence that since the 2007-2008 financial crisis, this particular aspect of globalization has slowed. This may partly be a result of events in the euro zone, where the sovereign-debt crisis triggered banks to cut back their lending to weaker economies (Melle, 2012). In fact, when financial flows and foreign direct investment were studied in 2015, cross-border volumes were only half 2007's level (Verma, 2016). Expectedly, the growth in global integration of financial markets prior to the 2007-08 financial crisis and its slow-down since has given rise

to many studies that investigate the mechanism through which equity market movements and volatilities are transmitted around the world. These studies make it clear that while real economic conditions and equity market performances are linked, the performance of equity markets vary based on international factors, so that market performance is not perfectly interconnected across countries (Yavas & Dedi, 2016). Markets become more closely correlated after unexpected events or shocks (Rezayat & Yavas, 2006a; Gray, 2009). An event in the US may not just affect US stock market alone. The consequences of such events may spillover to other countries.

Much of the earlier research in international stock markets focused exclusively on spillover of the co-movement between returns (Bekaert, Hodrick & Zang, 2009; Rezayat & Yavas, 2006; Yavas & Rezayat, 2008). These studies found little but increasing correlations between equity markets among different countries, thus providing attractive diversification opportunities. Similarly, Gray (2009) found financial contagion among emerging EU countries and concluded that their linkages strengthened after the 2007 crisis. More recent research (Dedi & Yavas, 2016; Kumar, 2013; Rey, 2013) confirms that information transmission is one of the reasons that affect volatility of stock prices. Henceforth, reviewing the transmission of stock market movements became a combined study of the spillover of prices as well as the volatility of prices. The interest rate volatilities have also increased after the two recent stock market crashes (dot.com bubble in 2000 and financial crisis of 2007-2008) which witnessed wide swings in asset prices. However, academic research on equity market volatility transmission has not been conclusive. For example, focusing on emerging markets, Scheicher (2001) stated that equity markets' return co-movements were significant but not their volatilities. Li (2007) examined the linkages between Shanghai and Shenzhen stock exchanges of China, Hong Kong and the United States, and found no spillovers (return

and volatility) between the stock exchanges in China and US markets, although unidirectional volatility spillover from Hong Kong to those in Shanghai and Shenzhen markets was significant. Other studies examining the spillover of information both in terms of return and volatility include Hamao, Masulis & Negev (1990), Christofi & Pericli (1999), Kumar & Mukhopadhyay (2002). They found intra-regional volatility spillovers to be more significant than the interregional spillovers.

## **1.2 Purpose of the study**

The purpose of this study is to investigate the linkages among equity markets of 3 major continents (North America, Europe and Asia) in terms of market returns and transmission/co-movement of volatility. Our aim is to empirically test the level of stock market interdependence in terms of return volatility spillover by:

- a. Setting up country-specific factors as control variables in the examination of stock market interdependence across countries.
- b. Incorporating the impact of news announcements on the volatility spillover across countries in the sample.

This thesis uses ARMA-GARCH framework in order to evaluate return volatility spillovers and ultimately help contribute to investment decisions.

## **1.3 Importance and motivation of the study**

The main motivation in this paper is to explore return and volatility linkages between USA, Eurozone and the Asian market by utilizing broad equity market indexes, and to

explore the effect of shocks to the markets by adding the economic surprise index, which can capture the effect of news and announcements. In examining the return co-movements, transmission and persistence of volatilities in county equity markets, we seek to understand if there are differences in different time periods in terms of return and volatilities and if there are opportunities for international investors/traders to earn a better return for a unit of risk.

This study is important because of the instruments used, and that it tackles several questions that remained unanswered in the literature. Earlier research were indecisive concerning the following questions:

1. Does the high rate of stock co-movement in major states of the world is due to interdependence of markets?
2. What is the effect of news and announcements on market returns and volatility spill-over?

From investors' perspective, a deeper understanding of how markets move together may result in superior portfolio creation and hedging strategies, while helping policy makers (especially central banks) gain an understanding of the processes and consequences of such spillovers. In other words, highlighting the impact of the information transmission process across equity markets is important for both micro (asset valuation and risk management) and macro (economic policy and risk management) agents. If market interrelations and connectedness are not understood, the results could include employment of inadequate or even counterproductive regulatory policies. Therefore, it is important to identify where volatilities arise from, how and where they are transmitted.

## **1.4 Layout of the Thesis**

The remainder of this thesis is divided into four main chapters, the next chapter, a review of former literature, focuses on offering a strong theoretical background, including the definitions and the development of the theories related to portfolio diversification and risk management. Furthermore, the study discusses the main findings and methodologies of earlier studies to explore the objective of this thesis and to develop the research question(s). In the light of chapter two, chapter three translates the research question(s) into hypotheses in the form of null and alternative. It also presents the sample to be studied, defines the variables and their sources. Then, it lays out the econometric methodology and the appropriate software packages used to test the underlying hypothesis that includes: Exponential GARCH, the simultaneous equation model, the two stage least squares approach as well as the three stage least square approach. Accordingly, chapter four delivers a detailed analysis of the descriptive statistics along with a comprehensive discussion of the empirical findings. The last chapter is the Conclusion of the Thesis and it summarizes the main findings of the study and its implications on portfolio managers. It also states the limitations of this dissertation and argues on the possibility of further research on the topic.

## CHAPTER 2

### THEORETICAL FRAMEWORK AND EMPIRICAL LITERATURE

#### 2.1 Theoretical framework

Diversification is not a new concept in economics and finance, in fact it can be traced back to the famous Miguel De Cervantes in 1605 who stated that: “Tis the part of a wise man to keep himself today for tomorrow, and not to venture all his eggs in one basket” (Cervantes, 1605). Unfortunately, diversification was not given any significant attention until 1939. Whilst the developed western countries like the US, Germany, and Great Britain were recovering from the crisis of the Great Depression of 1929, investors realized that diversification is an important financial concept in the financial world. It was more than a decade later, in 1952 when Harry Markowitz laid down the concept of diversification as “The process of spreading a portfolio across assets and thereby forming a portfolio” (Ross et al., 2008). In other words, within a diversified portfolio, while some of the holdings assets might be down and others might be up, the investor do fine overall. Hence, diversification would require that assets do not have a perfectly positive correlation, therefore; perfectly positive or nearly perfectly positive correlations between assets in portfolios are not considered an act of diversification.

Harry Markowitz became known as the Father of Modern Portfolio Theory (MPT) when he tried to formulate the concept of diversification mathematically. The main motivation behind his obsession with diversification relies heavily on the economic concept of opportunity cost and that all investment decisions are made in the face of trade-offs (Markowitz, 1952). The risk-return trade off facing investors was heavily addressed in the literature emphasizing that



an investor is not only concerned with his portfolio's expected return but also with the associated level of risks. Thus, the main assumption is that investors are risk averse and want to maximize their profits which means that they desire assets with high expected returns and low variability (low risk). Markowitz (1952) examined how an individual security contributes to the risk of the overall portfolio and affects its expected return. Additionally, Markowitz verified that a careful allocation of assets in a portfolio can maximize the expected return for a certain level of risk, or minimize the risk for a specified level of expected return (Markowitz, 1952). In other words, an investor can reach the same targeted expected return by selecting different types of investment assets (an efficient portfolio) that jointly have lower risk than an individual security. Consequently, it is crucial to portfolio managers to include the concept of diversification, as it contributes in adjusting both risks and returns, hence evaluating the relationship between risk and returns.

Furthermore, the actual return on any risk asset contains a normal part predicted by market participants and an uncertain part resulting from unexpected future news and announcements. The importance of an announcement depends on the amount of information, being expected or surprise, it delivers to the market (Kendal, 1953). Since the Efficient Market Hypothesis, which is concerned with expected announcements, dictates that prices already reflect all available information in the market, speaking about news means talking about the surprise part of an announcement (Rendleman, Jones, & Latané, 1982). The systematic risk represents market risk, it impacts a large number of risky assets in the market and cannot be handled or managed by firms and businesses; while the unsystematic risk or idiosyncratic risk influences a single firm or industry and can be controlled and managed with diversification (Bodie, Kane, & Marcus, 2014). Both the systematic risk adds up to the total risk. Wagner and Lau (1971), showed that diversification cannot eliminate portfolio risk but it can reduce it up to a

certain limit. Hence, while diversification can eliminate the unsystematic risk, systematic risk is not diversifiable. Actually, this restricted influence of diversification is due to the facts that assets are unprotected to common sources of market uncertainty such as inflation rates, exchange rates fluctuations, political instability, natural disasters and war that cannot be eliminated. However, a firm specific influence on two different assets differs, the two effects will offset each other's and increase risk adjusted returns (Brumelli, 1974). As a result of Markowitz theory, the Capital Asset Pricing Model (CAPM) was created later on and many researches helped introducing the CAPM to be the model that it is today starting by William Sharpe (1964), John Linter (1965) and Jane Mosin (1966). The CAPM quantifies a linear relationship between the expected return of an asset and its exposure to the market, assuming that the market portfolio is mean-variance efficient. The model draws on the Systematic Risk Principle: since investors are rewarded only for systemic risks and assumed that they deal with their unsystematic risk through diversification, and since rational investors should not bear a diversifiable risk, the expected return of a portfolio does not depend on the total risks, but only on the systematic (undiversifiable) risks. In other terms, risky assets with higher market risk are expected to yield higher returns. The supremacy of the CAPM to other models made the investors to adopt it as a practical tool to determine the fair price of an asset and the rate of return they deserve for exposing their money to risk. However, the CAPM relies on many assumptions that were deemed to be unrealistic. For example, it assumes that all information is publicly available and accessible to everyone, implying that investors will have homogeneous expectations with respect to risk and return; whereas in reality many investors have access to insider (private) information (Jaffe, 1974). The CAPM also considers that capital markets are perfect, assets are infinitely divisible, and can trade on public exchanges. Furthermore, the CAPM ignores the restrictions on borrowings by allowing market participants to borrow and lend at a common risk free rate, but this will lead them to

reach different optimal risk portfolios (Black, 1972). Although the CAPM was criticized by many studies for representing a highly simplified and idealized world (Fama & French, 1993; Merton, 1972; & Roll, 1977), it is still considered to be the foundation of all the subsequent asset pricing models. For instance, several empirical studies showed that the market risk term of the CAPM does not capture all the types of risk; hence, it ignores the complex nature of systematic risk. As a result, Ross (1976) proposed the Arbitrage Pricing Theory (known as APT) as an alternative model for pricing assets. “The APT models the expected return of a financial asset as a linear function of multiple macro-economic factors driven by the business cycle such as inflation rates and interest rate fluctuations”.

Unlike the CAPM, APT explicitly represents systematic risk, but the number and nature of the factors is likely to change over time and among economies. The three-factor model of Fama and French (1993) is a particular example where the expected return of an asset is a function of the market risk (as suggested by CAPM), the firm size (Banz, 1981), and book to market ratio (Chan & Karolyi, 1991). Nobel Laureate Eugene Fama and researcher Kenneth French (1992) developed an asset pricing model that expands on the capital asset pricing model (CAPM) by adding size risk and value risk elements to the market risk feature in CAPM. This model studies the statement that value and small-cap stocks outperform markets often. By adding these two additional elements, the model regulates for this outperforming tendency, which is thought to make it a better tool for evaluating manager performance. Fama and French highlighted that investors must be able to ride out the extra short-term volatility and periodic loss that could occur in a short time. Fama and French used thousands of random stock portfolios, and conducted studies to test their model and found that when size and value factors are combined with the beta factor, they could then describe as much as 95% of the return in a diversified stock portfolio. Given the ability to explain 95% of a portfolio's

return against the total market, investors can build a portfolio in which they receive an average expected return according to the comparative risks they accept in their portfolios. The key elements driving expected returns are market sensitivity, size, and connectedness to value stocks, as measured by the book-to-market ratio. Any extra average expected return may be credited to unpriced or unsystematic risk. Researchers have extended the Three-Factor model to include other elements. These elements comprise "momentum," "quality," and "low volatility," among others. In 2014, Fama and French changed their model to include five factors. Their model starts with the original three elements, whilst the fourth element enhances the concept of companies reporting higher future earnings have higher returns in the stock market, an element referred to as profitability. The fifth factor, referred to as investment, connects the concept of internal investment and returns together, suggesting that companies that steer profit towards major growth projects are likely to exhibit losses in the stock market.

The use of the above-mentioned asset pricing models and their extensions was primarily restricted to equity markets, especially equities traded in the USA. Since financial world is always evolving, triggering financial liberalization and financial globalization, portfolios also evolve as investors have wider choices than before. Indeed, the meaning of a well-diversified portfolio has transformed and changed over time, and an abundant number of empirical studies recognized the significance of international portfolio diversification (Rezayat & Yavas, 2006b). In fact, the issue of international portfolio diversification began in 1974 when Morgan Guaranty established the first investment of pension fund outside the USA (Zafaranloo & Sopian, 2013). The advantages of international diversification are due to the fact that different national stock markets may not be highly correlated, exhibit unsynchronized movements and respond to changes in the business cycle in opposite ways

(Grubel, 1968; Levy & Sarnat, 1970; Lessurd, 1973; Solnik, 1974; Jorion, 1985; and Levy & Lim, 1994). Since firms operating within the same industry or the same geographical region are subject to the same risks, portfolio diversification was extended to include assets from different stock markets across different countries. While global diversification was primarily limited to developed countries such USA and Western Europe, many emerging markets in Asia, Middle East and North Africa regions opened their doors later on to foreign investments and became globally accessible to investors due to financial innovation and technology (Bekaert & Urias, 1996). Moreover, several studies claimed that markets around the world became more and more integrated and increasingly interdependent as a result of the recent globalization, financial liberalization and deregulation (Beirn et al., 2009). Hence, the risk reduction benefits of international diversification will diminish (Byers & Peel, 1993). For instance, the boom in stock markets and their subsequent crash since 2000 have characterized financial markets worldwide. The robust co-movement has limited the benefits of international portfolio diversification (Rezayat & Yavas, 2006b). Therefore, investors considered alternative investment opportunities and broader portfolio diversification across multiple asset classes as a hedge to mitigate increasing risks. Asset allocation was heavily addressed in the literature as an efficient way to avoid excessive exposure to one source of risk. Understanding the nature of the interdependence between different asset classes is important for investors (Angkinand et al., 2010).

The concept of spillover of volatility, of asset returns, can be explained from the seminal work of Engle et al., (1990). He explained borrowing from meteorological vocabulary, the authors laid down the theoretical foundations for “own” and “cross” type spillovers. The “heat wave” theory, representing own-spillover, describes current volatility of a market as a function of past volatility of the same market (also sometimes referred to as volatility clustering). On the

other hand, the “meteor shower” hypothesis, signifying cross-spillover, describes current volatility of a market as a function of both past volatilities of the same market and past volatility from other markets (also called volatility transmission). It is to be noted that, the “meteor shower” definition of spillover includes both “own” and “cross” aspects. Empirically, it has been found that there is strong evidence in favor of own-spillover (Engle and Susmel, 1993). Almost all stock markets display “heat wave” type phenomenon. However, the same cannot be said about the “meteor shower” type spillover. The reason behind this could be linked to the origins of volatility spillover which lies in the interdependence of markets (Hamao et al., 1990; Fratzscher, 2002). When markets are integrated, individually, they can get affected by the news and events originating from each other’s socio-political, economic, legal, environmental, trade, commerce, and market innovation scenarios. It has been observed that markets that are integrated display cross-market spillover (i.e. meteor shower phenomena) in more pronounced manner. However, it has also been empirically found that markets that are not fully integrated show cross-market spillover mostly during a financial crisis, a phenomenon which a significant characteristic regarding volatility spillover, is the property of asymmetry (Glosten et al. 1993; Nelson and Foster, 1994). Like volatility of asset returns, the spillover of volatility also exhibits asymmetry with regards to the kind of news. Bad news seems to have severe effect on spillover (both own and cross) as compared to good news. This asymmetric property of spillover is a prime contributor to the cause of financial contagion. The study of volatility spillover is essential for two reasons: first, it relates to the notion of market efficiency. The “own” feature of spillover (heat wave phenomenon) is a straight result of the level of efficiency in the market. “Higher level of spillover indicates lower level of efficiency” (Bollerslev and Hodrick, 1992). Secondly, volatility spillover indicates the level of market integration. The “cross” aspect of spillover (meteor shower phenomenon) measures the degree to which markets are integrated (Engle and Susmel, 1993;

Bekaert and Harvey, 1995). An increase in interdependence among markets will result in higher cross-market spillover and greater chances of contagions occurring in the event of a financial crisis. In recent years, there has been a growing stream of literature related to volatility and its spillover between markets, which looks at the “contagion” aspect of it. Study of financial contagion involves analyzing the degree of co-movement between markets during financial crises (Claessens et al., 2001).

Different theories have discussed the direct effect of macroeconomic news on the volatility of stock prices. According to Becketti and Sellon (1989), many factors, such as inflation rates variations, monetary policies, and interest rate fluctuations may cause deviations in financial returns and increased volatility. Following the Autoregressive Conditional Heteroskedasticity (ARCH) model pioneered by Engel (1982) and Generalized (GARCH) by Borreslev (1986) a large body of the literature has been devoted to model the time-varying volatility in financial time series. According to Ross (1989), volatility signals the influx of new information. Even if the efficient market hypothesis holds (markets adjust to news perfectly and instantaneously), asset returns may exhibit volatility.

According to Ioannidis and Kontonikas (2006), monetary policy shocks (announcements) have a significant impact on stock market price change and stock market value. In other words, an expansionary monetary policy will lead indirectly to higher stock prices. Their results indicated that 80 % out of 13 OECD countries when faced with periods of tight monetary policy is associated with contemporary declines in stock market value, whereas interest rates increases are associated with lower stock prices via higher discount rates and lower future cash flows. Similarly, Rosa (2014) also showed that energy future prices and trading volumes are highly affected by monetary policy surprises.

More importantly, King and Wadhvani (1990) studied the crash of October 1987 and showed that price information flows across markets even when the information is market specific. They claimed that markets overreact to the events of another market beyond the influence of fundamentals; hence, they put forward the market contagion hypothesis. With the development of econometric tools, models have been extended to the multivariate dimension (MGARCH) (King & Wadhvani, 1990). This multivariate feature prompted the attractiveness of a new research topic: volatility spillovers. Volatility spillover is the transmission of shocks and financial distress from one market /region to another. In other words, the existence of volatility spillovers implies that a shock increases the volatilities not only in its own market, but in other markets as well. Dungey and Gajurel (2014) recently explored the different views regarding the definitions of contagion and transmissions of shocks. They pointed out that the normal interdependence between markets is not causing the shock, but it is propagating it and speeding up its transmission. In other words, when a shock hits a certain market, it does not only affect the market itself, but impacts the volatility of another related market. That's why studying volatility spillovers can help us understand how information diffuses across markets.

Exchange rate markets also exhibited volatility co-movements and proved to be linked to stock markets. For instance, according to Engle, Ito, and Lin (1990); Baillie and Bollerslev (1991) that shocks increased the conditional volatility of the British Pound, the Deutsch Mark, the Swiss Franc, and the Japanese Yen vis-a-vis the US Dollar. According to Kanas (2000), volatility spills over from stock market to exchange rates. Similarly, Chiang et al. (2000) pointed out that Asian stock markets are positively related to the value of the national currency. Fang and Miller (2002), supported the existence of a bidirectional causality



between the Korean foreign exchange market and the Korean stock market during the Korean financial turmoil of 1997 to 2000. Furthermore, Sabri (2004) showed that stock trading volume and currency exchange rate are the most related indicators of increasing stock return volatility and instability of emerging markets.

In Conclusion of the theoretical section of this Thesis, we showed that the concept of market spill-over and the impact of surprise announcements is linked and established in theory, previous research on the topic of market spill-over and impact of news announcements will be discussed in the Literature review.

## 2.2 Empirical Literature

“Most of previous research concludes that spill-over effects are significant only from the dominant market to the smaller market and that the volatility spillovers are unidirectional” (Bala & Premaratne, 2004). Early studies on volatility spillovers typically focus on equity markets in developed countries, and the transmission of volatility from large to small country markets. According to Eun and Shim (1989), the US market is the most influential stock market. Theodossiou and Lee (1993) found a high degree of interdependence and a statistically significant mean spillover from the US stock market to stock markets in Japan, U.K, Canada, and Germany. Bae and Karolyi (1994) demonstrated that when the asymmetric effect of bad news is ignored, the Japanese and the US stock markets exhibit significant transmissions of volatility. On the other hand, recent research on volatility spillover and stock market co-movement is currently still leaning on the concept that volatility spill-over effects are significant only from the dominant market to the smaller market but there is recognition that spill-over can be bidirectional and sometimes from smaller market to dominant market is rare but possible (Bala & Premaratne, 2004).

Xiao & Dhesi (2010) claim that the S&P 500 dominates the volatility transmission between the European and US stock markets. Furthermore, their results revealed that the UK market is the main transmitter of volatility within the European market. Researchers found evidence to prove that there is a mean-reverting process in the time varying conditional correlation among the European stock markets, which means EU countries are interdependent among each other to some extent and there is no serious contagion effect between them to provoke volatility spill-over. In addition, both conditional and unconditional correlation reveals that European stock markets are more dependent on each other. In contrast, the shock in

correlation from the US stock market tend to persist in European markets for a long period, in other terms, there is a contagion effect between US stock market and the European stock markets during crisis.

According to Dedi & Yavas (2017), significant volatility transmissions exist on the international stage, so they studied volatility spillover among major developed countries during crisis as well as during stable periods and evidence prove that during periods of crisis; volatilities are transmitted from the dominant market to other markets. The US is the main transmitter of volatility during period of crisis (1987, 2000, 2008), and that the sole country that transmits volatility to US during periods of crisis is the United Kingdom. In addition, the researchers also found evidence for volatility spillover during crisis periods from the German market to the French market, while the German market is affected of volatility spillover from the U.K and French markets. However, the only two countries that do not experience volatility spillover from other markets during stable periods are the USA and Italy, whereas the UK market exhibit volatility spill-over from USA; the German market experience volatility spill-over from France and UK, and the French market is affected by volatility spill-over from Italy and UK. The result of the mentioned study is in line with findings of other studies such as Yavas & Rezayat (2013), and Kiyamz (2003).

Slimane, Mehanaoui, & Kazi (2013), focused on return and volatility behaviour of stock markets. They found that the German market influences French and UK markets, especially during periods of crisis. Their results provided evidence of deep interdependence between European markets, which calls into question the benefits of investing in multiple European markets in order to diversify an investor's portfolio especially during periods of turmoil.

Their findings triggered serious questions concerning the role of market consensus versus information during times of crisis. According to Singh, Kumar, & Pandey (2008), there is greater regional influence in Asia when it comes to return and volatility spillover than EU and US. They claim that the Japanese market is the main transmitter of volatility in the Asian market and they are affected by volatility spillover from US and EU. Their findings are similar with the findings of Chuang, Lu, & Lee (2007) who analysed six Asian markets including Japan and found that the Japanese market is the least susceptible to volatility stimuli from other markets in the region. However, Japan is the most influential in transmitting volatility to other East Asian markets. In addition, they found a high degree of correlation among European indices namely FTSE, CAC, & DAX, which support the similar finding of many works such as Cheung & Westermann (2001), Melle (2003), Savva et al. (2004), and Birtram et al. (2007).

However, as emerging markets are gaining ground on the international stage and as international diversification is focusing investment in emerging markets, several researchers studied the linkages between developed markets and among emerging markets themselves. For example, Cheung and Cha (1998) empirically investigated the relationships between the four Asian Emerging Markets (AEM's): Hong Kong, Korea, Singapore, Taiwan, and the two largest markets in the world USA and Japan. They found that the US leads other equity markets but the four Asian emerging markets respond differently to the volatility in the US, the researchers found that innovations in US market influences Hong Kong and Singapore markets, but do not influence the Korean or the Taiwanese markets, whereas the Japanese influenced all the markets except the Korean.

In contrast, Bala and Premaratne (2004) found that it is plausible for volatility to spillover from the smaller market to the dominant one; their empirical study results indicate that there is a high degree of volatility co-movement between Singapore stock market and that of Hong Kong, US, Japan, and UK (respectively). Results found small but significant volatility spillover from Singapore into Hong Kong, Japan and US markets regardless of the last three being dominant markets. Brailsford (1996) provided evidence of bidirectional volatility transmission between the Australian and New Zealand equity markets.

Joshi (2011) found evidence of bidirectional return, shocks and volatility spillover among most of the stock markets in Asia. The low magnitude of volatility linkages found indicates the fragile integration of Asian stock markets. Furthermore, the paper adds to the argument that country's own volatility spillover is higher than cross-market spillover, and explains that the repercussion of weak integration will make investors witness a reduction in diversifiable risk. In addition, the paper also found evidence of unidirectional cross-market asymmetric responses spillover from India to Korea, Hong Kong to India, Japan to India, and China to Korea. Li & Giles (2013) found that the US stock market has unidirectional shock spillovers to both Japanese and the Asian emerging stock markets.

In addition, Li (2012) showed that China's stock market reforms allowed spillovers from China to the US, Korea, and Japan. Moreover, Gunasinghe (2005) found a low volatility spillover effect from the Indian stock market to other regional stock markets, like Sri Lanka and Pakistan. Similar work was done in the MENA region and according to Abraham and Seyyed (2006), they observed a flow of information risk from the Bahraini market to the less accessible Saudi market at the time. Later on, Morana and Beltratti (2008) claimed that co-

movements of prices, returns, volatilities and correlations between the developed markets of the USA, UK, Germany, and Japan are increasing over time.

Jang & Doong (2004) tested for mean and volatility spillover from one market to another in the G7 countries and searched for evidence of asymmetry; which means, whether negative shocks starting in a stock market (foreign exchange market) apply more or less impact on the foreign exchange market (stock market) than a positive shock of equal magnitude. Their results showed that movements of stock prices affect future exchange rate movements but changes in exchange rates have less direct impact on future changes of stock prices, furthermore, their empirical evidence suggests that there is information flow (transmission) between the two markets and that the two markets are integrated. Moreover, Ben Saiida et al. (2018) utilized in their paper a generalized variance decomposition technique, and incorporated a fast-tractable Markov regime-switching framework into the vector autoregressive (VAR) model. Their Empirical investigation on volatility indices of eight developed financial stock markets shows that the total and directional spillovers are more intense during turbulent periods, with frequent swings between net risk transmission and net risk reception. Conversely, during periods of tranquillity, volatility spillovers are relatively moderate.

### **2.2.2 Impact of news announcements on financial markets**

In recent years, a number of studies addressed the impact of news announcements on the volatility of some markets and the volatility spill-over across markets. According to Rossi (1998), US macroeconomic announcements affect UK government securities prices and that the change is between 2 to 6 basis points in government bond yield before news releases, on

the day of the releases or immediately after it, depending on the economic indicator underlying the news announcement. Fleming and Remelona (1999) studied the impact of information arrival in the US treasury market on prices and trading activity in financial markets, focusing on scheduled announcements. They find that information arrival has a considerable effect on prices and subsequent trading activity especially in periods of high uncertainty. Balduzzi, Elton & Green (2001) investigated the impact of scheduled economic announcements on the price, volatility and volume of four US treasury bonds. They use Money Market Services (MMS) data to calculate the surprise component in economic announcements. They find that 17 news releases significantly affect the price of bonds, with labor market, inflation, and durable goods orders having the most distinct effect. Their results show that the magnitude of the impact depends on the maturities of the bonds, that public news is incorporated into prices within one minute or less, that volatility increases immediately after the announcements and remain high for up to 60 minutes and that surprise explains a significant part of price volatility.

Andersen et al. (2003) examined the impact of macroeconomic news on the US dollar exchange rate. Their results indicate that the news and intra-day movements of the US dollar are significantly correlated, and that the impact is greater when the surprise element is greater; good news have a smaller impact than bad news, and that announcements timing is important and crucial. According to Brenner, Pasquariello, and Subrahmanyam (2009), the arrival of surprise economic news has a statistically and economically significant impact on the US financial markets, but also that this impact varies greatly across asset classes. Conditional stock return volatility decreases on the trading day before, increases on the day when the announcements are made, and subsequently decreases. “Conditional bond return volatility rises before the news is released and drops afterward”. This effect is stronger for

shorter maturity bond portfolios. They claim that the estimated shifts in volatility appear to be persistent in the short run. The effect of news is asymmetric since their absolute magnitude is generally greater when the macroeconomic information released represents bad news. Conditional mean excess holding period returns for stocks and bonds are instead mostly positive to the release of unexpectedly good news, but the paper offer little or no support for the commonly held notion; that the arrival of news is accompanied by greater co-movement among asset returns and that the return co-movement often decreases with announcement especially if it is bad news.

Other researchers such as Jiang, Konstandini, and Skiadopoulos (2012) tried a new approach where they used scheduled news vs unscheduled news instead of using good news and bad news. They examined the effect of US & European news announcements on the spillover of volatility across US and European stock markets. They found significant spillovers of implied volatility between US and European markets as well as within European markets. They observed a stark contrast in the effect of scheduled versus unscheduled news releases. “Scheduled (Unscheduled) news announcements ends (create) information uncertainty, leading to a decline (rise) in implied volatility”. They claim that the results were robust to extreme market events such as the 2008 financial crisis and that the results prove volatility contagion across markets. They concluded their paper by claiming that although news announcements do affect the degree of volatility spillover, they do not fully clarify the volatility spillovers. As for emerging markets and their reaction to news announcements, Li and Giles (2013) claim that for both the long run and the short run, the emerging markets are more affected by their own past shocks, as compared to developed markets, and their result indicates that emerging markets seem to be more affected by “good news”. Nevertheless, the researchers concluded that it does not matter which market is examined, because the negative



effects are always stronger in the overall effect. According to Stankeviciene and Akelaitis (2014), types and categories of public announcements do not play essential role when determining the relation between values of stock prices and stock price changes as the average abnormal returns estimated for all the categories as well as both of the types were higher in lower price ranges and vice versa. Nevertheless, the categories and the types of public announcements did have different impacts on stock prices. Higher average abnormal returns were estimated for the news of positive content than for the news of negative content (the difference varies from 0.02 percents to 1.05 percents in different price ranges), which might suggest that a more remarkable reaction of investors should be associated with the good sentiment of news.

## **2.3 Conclusion**

In this chapter, we examined the theoretical grounds and reviewed previous research concerned with detecting and understanding co-movements of returns across different financial markets. According to previous research in the literature, we concluded that the US is the main transmitter of volatility during all the major crises. In addition, that volatility spill-over used to be only unidirectional from the dominant market to the smaller one, but with the help of financial liberalization and the continuous integration of markets; strong evidence suggests that volatility spill-over can be bidirectional in some instances. Previous research on volatility spill-over across different markets provided strong evidence of deep interdependence between several European markets, and that the Japanese market is the main transmitter of volatility in the Asian market. On the other hand, previous research on impact of news announcement on financial markets provided strong evidence that the arrival of surprise economic news has a statistically and economically significant impact on the US

financial markets, but also that this impact varies greatly across asset classes. Furthermore, co-movement of return often decreases with announcement especially if it is bad news, and that news announcements do affect the magnitude of volatility spill-over.

In chapters to come, we will extend on the previous work done on the topic, focusing on the direct volatility spillover between the three markets, and illustrating the impact of macroeconomic news announcements on return volatility spillover between financial markets. It is worth noting that macroeconomic announcements themselves do not have a significant effect on markets unless they do not meet expectations. For this reason, we will focus in our study on the surprise element of these announcements, that is, the degree to which an announcement deviates from market expectations.

## **CHAPTER 3**

### **PROCEDURE AND METHODOLOGY**

#### **3.1. Introduction**

In the previous sections of this thesis, we showed that the concept of market volatility spillover and the impact of surprise announcements are linked and established in theory. In addition, we examined the theoretical grounds and reviewed previous research concerned with detecting and understanding co-movements of returns across different financial markets. According to previous research in the literature, we concluded that the US is the main transmitter of volatility during all the major crises. In addition, volatility spillover used to be only unidirectional, meaning that volatility is spilled from the dominant market to the smaller one, but with the help of financial liberalization and the continuous integration of markets; strong evidence suggests that volatility spillover can be bidirectional in some instances. On the other hand, previous research on impact of news announcement on financial markets provided strong evidence that the arrival of surprise economic news has a statistically and economically significant impact on the US financial markets, but this impact varies greatly across asset classes.

#### **3.2 Research Question**

First, do stock markets of US, EU, and Asia experience financial interdependence, and if so, do they exhibit return volatility spillover?

Secondly, do macroeconomic news announcements influence volatility spillover across US, EU and Asia's stock markets?

### 3.3 Hypotheses

According to the previously established literature and to the formulated research questions, this section presents the testable hypotheses underlying this study.

**H<sub>a0</sub>:** US, EU and Asian markets are not interdependent and do not exhibit return volatility spillover.

**H<sub>a1</sub>:** US, EU and Asian markets are interdependent, and exhibit return volatility spillover.

The null hypotheses ( $H_{a0}$ ) implies no integration among US, EU and Asian markets, such that the volatility in stock Y is not affected by volatilities in stocks  $X_1, \dots, X_n$ . This can be confirmed by testing the significance of the coefficients for return volatilities in stocks  $X_1, \dots, X_n$ .

**H<sub>b0</sub>:** Economic news do not affect US, EU, and Asia's stock markets returns and volatility spillover.

**H<sub>b1</sub>:** Economic news affect US, EU, and Asia's stock markets returns and volatility spillover.

The null hypothesis ( $H_{b0}$ ) indicates that news announcements have no impact on stock market returns and that the return in stock Y is not affected by a macroeconomic surprise. This can be confirmed by testing the significance of the coefficient of the economic surprise index.

### 3.4 Population and Data sample

This section describes the sample used, defines the variables and the source of the data. However, there was some discrepancy in the data at first. The number of observations in the dependent and independent variables were mismatched, so we filtered the data by eliminating the observations that were present in one and not present in the other.

The sample size of the study is from January 3<sup>rd</sup> 2000 till March 19<sup>th</sup> 2019, a total of 4,936 daily observations.

#### 3.4.1 Variable Description and Sources

The daily returns are defined as follows:

$$r_t = \frac{S_t - S_{t-1}}{S_{t-1}}$$

But, returns for these three assets will be calculated using the log return which is equivalent to the previous method

$$r_t = \ln \frac{S_t}{S_{t-1}}$$

Where  $s_t$  is the stock market index in day t and in day t-1.

Three market indices have been chosen for this study representing the various Financial markets. Thomson Reuters United States index, Thomson Reuters Asia Pacific index (includes: Japan, China, India, Indonesia, Malaysia, Singapore, South Korea, Vietnam, and others), and Thomson Reuters Eurozone 50 index (includes: France, Germany, UK, Ireland, Netherlands, Italy, and others). These indices are "optimized" and built on modern portfolio theory to depict the best investment outcome for various levels of risk.

**Economic Surprise Index:** Based on Chapter two, academic studies have found that asset prices respond to regularly scheduled economic announcements and exhibit changes in their return volatility patterns with daily wings highly exceeding historical standards. An economic news surprise is an episode whereby actual macroeconomic news data releases exceed or fall short of market expectations (its forecasted value). While most researchers have concentrated their studies on the response of the asset to one or few economic data releases, our thesis finds that an aggregated index of U.S. data surprises can be very helpful in anticipating future trends in U.S. economic activity as well as the underlying trends in the transmission of return volatility among different stock markets. In fact, when US economic activity is rising or falling, the tendency of economists to underestimate this move on both the upside and the downside leads to a sharp and persistent trend in economic surprises. This is due, first, to the fact that the median forecast of surveyed economists might be biased to show little change as it tends to balance both bullish and bearish economic forecasts. Second, forecasters might be slow to adjust their forecasts when economic conditions are changing, perhaps because their expectations are anchored to lagged data rather than future economic data. Third, in the face of uncertainty, forecasters might become conservative and not adjust their forecasts quickly enough to changing conditions.

We retrieved the daily data of the Bloomberg Economic Surprise Index from 3 January 2000 until 19 March 2019 from Bloomberg Database. “The surprise element is calculated as the percentage difference between the actual economic data release and the median of forecasts for that release, smoothed with six-month decay”. This index is based on Bloomberg News surveys of economic analysts for 39 U.S. weekly and monthly time series reported on a regular basis on the economic calendar. The six-month decay is a weighted average calculated by assigning each release a relative weight with more recent releases given a

higher weight. Days with missing values are treated as no surprise days, thus the corresponding dummy variable will be equal to zero in such days. The Bloomberg's synchronized survey data on market expectations of macroeconomic news consists of median expectations of the survey panellists. Anderson et al. (2009) tested for the unbiasedness of the Bloomberg forecasted data using standard techniques used in the literature (Balduzzi et al., 2001) and found that the survey expectations are of good quality (null hypothesis of unbiased data could not be rejected at 10% level).

The following sample of macroeconomic news announcements is the most used and influential in the most academic studies and press. (A partial list of the announcements is found in the Appendix)

- **Consumer Price Index:** Consumer prices are a measure of prices paid by consumers for a market basket of consumer goods and services. The yearly (or monthly) growth rates represent the inflation rate.
- **Target Federal Funds Rate:** The federal funds rate is the short term interest rate targeted by the Federal Reserve's federal open market committee (FOMC) as part of its monetary policy.
- **Unemployment Rate:** The unemployment rate tracks the number of unemployed persons as a percentage of the labour force (the total number of employed and unemployed). These figures generally come from a household labour force survey.
- **Non-Farm Payroll:** This indicator measures the number of employees on business payrolls. It is also sometimes referred to as establishment survey employment to distinguish it from the household survey measure of employment (Bloomberg, 2019).

### 3.5 Diagnostic tests

For the results not to be false, our data series should be stationary. Moreover, the GARCH family models can be applied in cases where the data series are heteroskedastic. To avoid obtaining misleading results, a range of diagnostic tests will validate the specified series.

#### 3.5.1 Augmented Dickey-Fuller (ADF) for stationarity

A series is stationary, if the distribution of its values does not change over time, that is, if the probability that  $y$  falls within a particular interval is the same at any point in time. For non-stationary series, previous values of error term will have a non-decaying effect on the current value of  $y$  as time progress (Brooks, 2012). The results will then be false, meaning that they may indicate a relationship that is not actually valid. To test for the stationarity of the data series, we will use the Dickey-Fuller (DF) and the Augmented Dickey-Fuller (ADF) unit root tests.

#### 3.5.2 Ljung-Box test for autocorrelation

The Ljung-Box test is used to assess the presence of autocorrelation in a time series. More specifically, it is used to test for autocorrelation in the residuals at multiple lags jointly.

In the model  $\varepsilon_t = c + p_1\varepsilon_{t-1} + p_2\varepsilon_{t-2} + \dots + p_p\varepsilon_{t-p} + u_t$

The test consists of testing:

$$H_0: p_1 = p_2 = \dots = p_p = 0$$

$$H_1: \exists p_i \neq 0 \text{ for } 1 \leq i \leq p$$



$H_0$ : The residuals are independently distributed, that is, there is no autocorrelation up to lag  $p$

$H_1$ : The residuals are correlated

Simulation studies suggest that choosing  $p \approx \ln(T)$  where  $T$  is the total number of observations provides better power performance (Tsay, 2010).

### 3.5.3 Jarque-Bera test for normality

It is very useful and important to inspect the normality assumption of both the variables and the errors. Normality of the errors describe if the regression is linear or not, and the normality of the variables infers if the sample of data chosen should be increased or not. “Skewness is a measure of how symmetric the observations are around the mean, and kurtosis is a measure of the thickness in the tails of a probability density function” (Balanda & MacGillivray, 1988). For a normal distribution, the skewness is 0 and the kurtosis is 3.

The Jarque-Bera test for normality is:

$H_0$ : *Skewness* = 0 , *kurtosis* = 3 (normal distribution)

$H_1$ : *Skewness*  $\neq$  0, *Kurtosis*  $\neq$  3 (not normal distribution)

### 3.5.4 ARCH test for heteroscedasticity

The ARCH test was originally devised by Engle in 1982 and is comparable to the Lagrange multiplier (LM) test for autocorrelation. The error terms  $\{\varepsilon_t\}$  are said to be conditionally heteroscedastic if their conditional variance is not constant over time (Engle, 1982).

in the model  $\varepsilon_t^2 = c + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_p \varepsilon_{t-p}^2 + u_t$

The arch test is as follows:

$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_p$  (the residuals are homoscedastic, hence; no arch effect)

$H_1: \exists \alpha_i \neq 0 \text{ for } 1 \leq i \leq p$  (the residuals are heteroskedastic)

where  $\{\varepsilon_t\}$  are the residuals of the linear regression

$y_t = c + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \dots + \beta_k y_{t-k} + \varepsilon_t$ , in which  $y_t$  is the series under study.

### 3.5.5 Model checking

We need to make sure that we examine the fitted models very carefully and check for probable model inadequacy during the modeling process.

If we already have adequate model fitted on data, then we expect that the residuals series should be recognized as a white noise. We can also use the other tests such as BDS test of independence on the residual series for that purpose. We explain the methods of the BDS test later in this chapter. In order to make sure that the residuals series is a white noise, we use the Ljung-Box statistics to test for the closeness of  $\hat{a}_t$  to a white noise, using the ACF. If we realize that the fitted model is inadequate, then we should refine the model. For example, we may need to simplify the model and aim to remove the insignificant parameters from the model, and use the information criteria to make sure that we reach the suitable fit that is an adequate one.

**Autocorrelation Function for MA models:**

When working with a moving average process, we are confident that a MA( $q$ ) series is only linearly associated to its initial  $q$ -lagged values and henceforth is a “finite-memory” model, meaning that any correlation dies out in after new lags. To identify the order of an MA process, we check its ACF. The ACF of an MA( $q$ ) process is not significant at an order equivalent or greater than lag  $q + 1$ . To test the significance of the ACF, we draw the correlogram. If the ACF is inside the confidence interval, then it is not significant.

**Partial Autocorrelation Function (PACF) for AR models:**

The PACF of an AR( $p$ ) process is not significant at an order equal or greater than  $q + 1$ . To test the significance of the PACF, we draw the correlogram. If the PACF is inside the confidence interval, then it is not significant.

**Non-linearity Test: BDS Test**

We should check for the existence of the independence and identical distribution (i.i.d) assumption of a time series using Brock, Dechert, and Scheinkman (1987) test statistic, that is commonly known as BDS test. As BDS test has a good power against a broad range of data, we can use this test to investigate the processes that are departed from the property of i.i.d. Brock, Scheinkman, Dechert, & LeBaron, (1996), claim that the BDS test is a common method to apply to the standardized residuals of GARCH models. The standardized residuals are the residuals divided by their respective standard deviations. Standardized residuals are used to standardize normal distributions in order to compare values. There is some consideration on the application of the BDS test. For instance, in order to avoid

committing type I error, the data should be a stationary process. Consequently, we may need to test for the unit root, and also “In running the empirical tests, it is recommended to do some bootstrap experiments” (Racicot, 2012). The null hypothesis of the test is defined as the series under investigation is an i.i.d. process. In order to use the BDS test on the residuals of our GARCH models, there are some considerations that must be expressed. Residuals are used to test the significance of models by the BDS test, however, for the GARCH models the results may not be satisfactory, so the literature recommends considering the standardized residuals of the GARCH models for the BDS test (de Lima, 1996).

### **3.6 Empirical Methodology**

The aim of this section is to describe the econometric models used to address the research question. We derive the volatility of the stock returns from a GARCH model, and then a simultaneous equations model is estimated using a three-stage least squares (3SLS) approach.

#### **3.6.1 ARMA-GARCH model**

In quantitative financial research, the most commonly used empirical methodology to model and forecast time-varying volatility is the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH). In this thesis, we employ a univariate GARCH to model the volatility of daily returns on each of the market indices chosen for the study. What follows is a description of the historical and theoretical grounds of the GARCH model.

The occurrence of volatility clustering takes place when the market data witness periods of relative calm and periods of high volatility, whereby large and small errors tend to occur in

clusters (Vogelvang, 2005). Although there is no universally accepted explanation of it, this phenomenon can be modelled. To capture such volatility clustering, Engle (1982) introduced the Auto Regressive Conditional Heteroskedasticity (ARCH) model based on the notion that the volatility is not constant, and that the information from the past might influence the conditional disturbance variance.

Under an ARCH (p) process, recent disturbances affect the variance of the current disturbances and thus the variance of the dependent variable. Since then, the ARCH model was successfully applied to volatile markets. It was extended later on by Bollerslev (1986) who proposed the Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model. In a GARCH (p, q) model, the conditional variance of the coming period is a linear function of a long term weighted average, previous periods squared residuals (the ARCH term) and its own lag (forecasted variance from the last period, i.e. the GARCH term). The key elements of Bollerslev's model are defined by an Autoregressive Moving Average (ARMA) method, conditional variance, and heteroscedasticity. returns until  $t-1$  are denoted by  $I_{t-1}$ . Subsequently, heteroscedasticity (from ancient Greek *hetero* means "different" and *scedasis* means "dispersion") indicates that the variance of a certain variable is not constant over time. In addition, the GARCH model is thought to be an ARMA process where the variance is a function of previous squared errors (Moving Average) and previous values of itself (Autoregressive) (Bollerslev, 1986). The mean of the GARCH model can be an ARMA process, and the variance as GARCH equation. The ARMA(p,q)-GARCH(r,s) model for the process is represented in the following equations:

Mean Equation:

$$Y_t^i = \alpha_0 + \sum_{j=1}^p \alpha_j Y_{t-j} + \sum_{k=1}^q \beta_k \varepsilon_{t-k} + \varepsilon_t + Y_t^j + Y_t^k + B.E.S.I$$

Variance equation:

$$\sigma_t^2 = \delta_0 + \sum_{l=1}^r \delta_l \sigma_{t-l}^2 + \sum_{m=1}^s \gamma_m \varepsilon_{t-m}^2 \quad / I_{t-1} \sim N(0, \sigma_t^2)$$

$(Y_t^i, Y_t^j, Y_t^k)$  are the returns of stock markets in US, EU, and Asia respectively at day t

$\sigma_t^2$  is the conditional variance,  $\sigma_t$  is the volatility.

### 3.6.2 Exponential GARCH (EGARCH)

Nelson (1991) introduced EGARCH model to get rid of the main threats of the GARCH model. First, to ensure the positivity of the variance, EGARCH takes the natural logarithm of the variance instead of the variance itself, so the parameters may have negative signs, but the variance will stay positive. Moreover, he included an extra parameter that capture the asymmetric effect, so it distinguishes the effect of negative shocks from that of positive shocks (Nelson, 1991).

Given  $z_t \sim N(0,1)$  and  $[|z_t|] = \sqrt{2/\pi}$ , then  $g(z_t) = \theta z_t + \gamma(|z_t| - \sqrt{2/\pi})$  where

$(|z_t| - \sqrt{2/\pi})$  characterises the deviation of  $z_t$  from its expected value and  $g(z_t)$  is a function of  $z_t$  and denotes the response to shocks. If  $z_t > 0$ ,  $g(z_t)$  is linear with a slope of  $\theta + \gamma$ , and if  $z_t < 0$ ,  $g(z_t)$  is linear with slope of  $\theta - \gamma$ . This will differentiate positive from negative shocks.  $\theta = -\gamma$  denotes the reply to a negative shock.

Therefore, the ARMA-EGARCH model for our study can be written as:

Mean equation:  $Y_t = \alpha_0 + \sum_{j=1}^p \alpha_j Y_{t-j} + \sum_{k=1}^q \beta_k \varepsilon_{t-k} + \varepsilon_t$ ,  $\varepsilon_t = \sigma_t z_t$

Variance equation:  $\ln(\sigma_t^2) = \omega + g(z_t) + \beta \ln(\sigma_{t-1}^2)$

The long term log variance is:  $\ln \bar{\sigma}^2 = \omega / (1 - \beta)$

So the long term variance could be calculated by taking the exponential of  $\ln \bar{\sigma}^2$ .

The estimation of the EGARCH's parameters is almost identical to the estimation of the GARCH parameters. They are estimated by maximizing the log-likelihood function that is denoted in the following equation:

$$\ln L(\omega, \theta, \gamma, \beta) = -0.5 \sum_{t=1}^T \left[ \ln(\sigma_t^2) + \left( \frac{\varepsilon_t}{\sigma_t} \right)^2 \right]$$

### 3.6.3 Simultaneous equation models (SEM)

According to Chiandotto and Bacci (2018), the simultaneous equation model is a compound of equation models where explanatory variables from one equation can be dependent variables in other equations. A variable is defined as endogenous if it can be clarified in another equation, which belongs to a complete simultaneous equation model (SEM). Furthermore, in an SEM; the endogenous explanatory variables are explicitly specified in a structural equation. Since endogenous explanatory variables are correlated with the disturbance terms in all the structural equations of the SEM, Ordinary Least Squares will be unpredictable; thus, the consistency property of the OLS is lost (Vogelvang, 2005).

### 3.6.4 Estimation methods for a simultaneous equation model (SEM)

We differentiate between two kinds of estimation methods for a SEM: single equation methods and full information methods. A single-equation method, such as the two stage least squares (2SLS) estimator, and the full information method such as the 3SLS. Although they are both consistent methods but the 3SLS is both consistent and asymptotically efficient.

We will use the three stage least square approach in our work.

Our model is as follows:

$$\text{Volatility US} = \omega_1 + \alpha_1 \text{Vol. US (-1)} + \beta_1 \text{Vol. EU} + \gamma_1 \text{Vol. Asia} + \theta_1 \text{Vol. EU (-1)} + \varphi_1 \text{Vol. Asia (-1)}$$

$$\text{Volatility EU} = \omega_2 + \alpha_2 \text{Vol. EU (-1)} + \beta_2 \text{Vol. US} + \gamma_2 \text{Vol. Asia} + \theta_2 \text{Vol. US (-1)} + \varphi_2 \text{Vol. Asia (-1)}$$

$$\text{Volatility Asia} = \omega_3 + \alpha_3 \text{Vol. Asia (-1)} + \beta_3 \text{Vol. US} + \gamma_3 \text{Vol. EU} + \theta_3 \text{Vol. US (-1)} + \varphi_3 \text{Vol. EU (-1)}$$

The volatility term is the specified conditional variance.

### Two stage Least Squares

The structural equation of SEM contains regressors that are correlated with the error term. There is always a source of biasness in the equation and is referred to as simultaneity bias. To mitigate this bias, it is ideal to replace the endogenous regressors with instruments. The instruments are constructed from the predetermined regressors and the method is termed two-stage least squares (2SLS) estimation, in which:

**Stage 1:** Regress the endogenous variables on the exogenous variables using OLS. Save the fitted values for the endogenous regressors.

**Stage 2:** Estimate the structural equations using OLS, but replace any right-hand side endogenous variables with their stage 1 fitted values (Vogelvang, 2005).



### **Three stage Least Squares (3SLS) Estimator**

The principle of 3SLS is a combination of the 2SLS and the Seemingly Unrelated Regression (SUR) model. The three-stage least-squares approach is a reconfiguration of the two stage least squares method to take into account the correlations across equation disturbances in the same way that SUR generalizes OLS (Chiandotto and Bacci, 2018).

The 3SLS estimator contains the following 3 stage procedure:

**Stage 1:** Regress the dependent variables on the independent variables using OLS. Save the fitted values for the dependent regressors.

**Stage 2:** Estimate the structural equations using OLS, but replace any right-hand side dependent variables with their stage 1 fitted values and then save the 2SLS residuals.

**Stage 3:** Estimate the variances and covariances of the disturbance terms (cross equation correlation matrix). Apply the SUR estimator.

The 3SLS is reliable and asymptotically more resourceful than the 2SLS. Thus, it yields more appropriate results.

Although the 2SLS and the 3SLS were historically estimated following the above stages, estimates are now computed in one formula programmed in econometric software packages (Vogelvang, 2005).

### **3.7 Statistical and Econometric Packages**

In order to estimate the EGARCH models and the two stage least square and three stage least square approach, we rely on “E-VIEWS” version 7.

### **3.8 Conclusion**

In this chapter, we described the sample and defined the variables and their sources. Moreover, we clarified the methodologies and addressed the econometric tools that will be employed to test the level of integration among financial markets, as well as the impact of announcement surprises.

## CHAPTER 4

### DATA SET AND EMPIRICAL RESULTS

#### 4.1 Data set

For the empirical analysis, we utilize daily data for the previous 19 years starting in January 3, 2000 till March 19, 2019. The choice of this period is partly determined to capture return volatility spill-over of major and significant financial/economic crises such as the dot com bubble, the 2008 financial crisis, and the market plunge of 2018 and of course the availability of data on the Bloomberg Economic Surprise Index (BESI). The BESI calculates the surprise values and index of 39 of the most watched U.S economic releases. It shows the degree to which economic analysts under- or overestimate the trends in the business cycle. The surprise element is defined as the percentage difference between the actual economic release and the median of analysts' forecasts for that release, levelled with a six-month decay. This six-month decay is a weighted average calculated by assigning to each release a relative weight with more recent releases given a higher weight. The values of the BESI are Z-scores, which represent the number of standard deviations that analyst expectations lie above or below normal surprise levels ( $(actual\ releases - Bloomberg\ survey\ median) / standard\ deviation$ ). (Bloomberg, 2019). The BESI shows how well the data meet economic expectations. A positive value indicates that data are better than expected, a null value indicates that data meets expectations, and a negative value indicates that data is worse than expected. Furthermore, our main hypothesis for this study is that the U.S.A is the most influential stock market in the world, and that shocks to its stock market originate via news announcements,

and that the return volatility occurring in US is transmitted to EU and Asia which is a transmission of volatility in developed markets because of interdependence of these markets.

**Table 1: Q statistic test and ADF results**

<b>Variables</b>	<b>Q statistic</b>	<b># of lags</b>	<b>ADF t statistic</b>
<b>Price. USA</b>	26.085	5	0.631816
<b>Price. E U</b>	0.8282	1	-2.363144
<b>Price. Asia</b>	9.9837	5	-2.797090
<b>Return. US</b>	0.00008	1	-53.71491***
<b>Return. E U</b>	0.0007	1	-51.67680***
<b>Return. Asia</b>	0.0021	1	-85.28964***
<b>B.E.S.I</b>	0.0080	1	-16.71559***

\*: significant at 10%    \*\*: significant at 5%    \*\*\*: significant at 1%

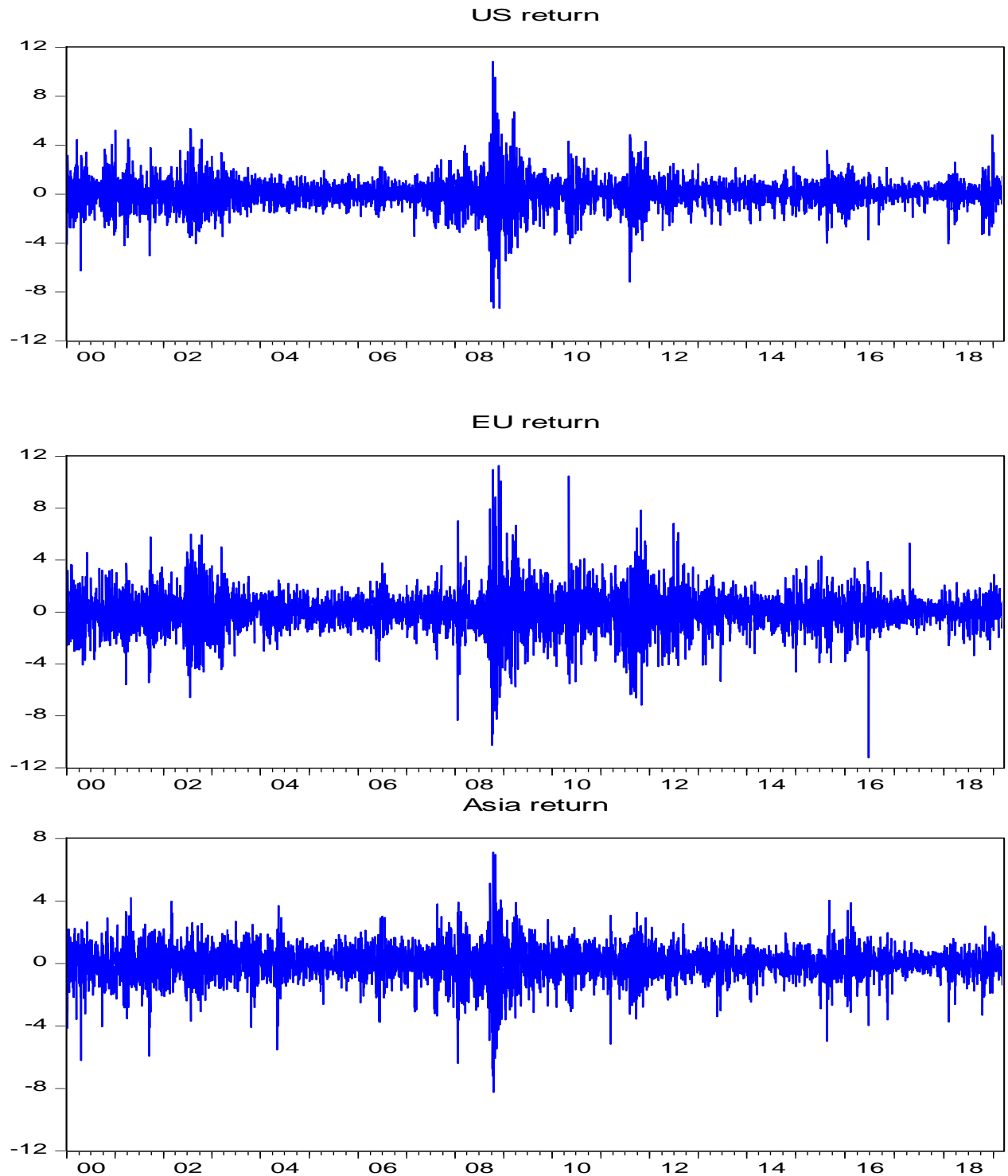
To begin our empirical analysis, we should first test our data for any anomalies such as unit root (stationarity). First, we will utilize the Q statistic on the residuals to detect the number of lags needed for the ADF test.

$H_0$ : unit root exists in the series

$H_1$ : no unit root in the series

The price series turns out to be non-stationary<sup>1</sup> while the return series are stationary and do not have a unit root. We will use the return series to conduct this study

**Figure 1: Return series plot (2000-2019)**



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<sup>1</sup> The three price series are stationary at 1<sup>st</sup> difference.

Figure 1 shows the movement of returns in USA, EU, and Asia during the period under consideration. The series does not show any trend, but shows high volatility and a sensitivity to major events mainly the 2008 (The plunge of 2018 and the 2000 stock market crash are also visible in all three markets). These return series show volatility clustering (periods of high volatility is followed by high volatility for a certain period and periods of low volatility is followed by low volatility for a certain period).

**Table 2: Descriptive statistics**

	<b>USA</b>	<b>EU</b>	<b>Asia</b>	<b>B.E.S.I</b>
<b>Mean</b>	0.015201	0.003477	0.006666	0.011384
<b>Median</b>	0.032519	0.025322	0.045020	0.000000
<b>Maximum</b>	10.84037	11.28545	7.113481	0.991000
<b>Minimum</b>	-9.330356	-11.23508	-8.248173	-0.996000
<b>Std. Dev.</b>	1.189599	1.533268	1.057118	0.297748
<b>Skewness</b>	-0.238771	-0.114390	-0.587254	0.020419
<b>Kurtosis</b>	11.20919	8.850790	8.109040	4.035917
<b>Jarque-Bera</b>	13904.13***	7049.664***	5650.937***	221.0487***
<b>JB-Probability</b>	0.000000	0.000000	0.000000	0.000000

Table 2: descriptive statistics regarding the daily returns on United States index, Eurozone 50 index, Asia Pacific index, and Bloomberg Economic Surprise Index.

Table 2 shows that the mean of returns on the US index is 1.52% with a standard deviation of 1.1896. The maximum return reached 10.84 \$ while the minimum was -9.33\$. Going

further into the description of this return distribution, the return series witness a high kurtosis of 11.2 indicating that the distribution is leptokurtic. Table 2 also shows that the mean of returns on the Euro index is -0.00348 with a standard deviation of 1.53. During the sample period the maximum return reached 11.28\$ while the minimum was -11.23\$. Kurtosis equal to 8.8 far from the normal 3. Skewness is equal to -0.11 which means the distribution is skewed to the left. Whereas the mean of returns on the Asian index is 0.00667 with a standard deviation of 1.05. The maximum return reached 7.1\$ while the minimum was -8.2\$. Skewness is equal to (0.58) which means the distribution is skewed to the left. In addition, kurtosis is equal to 8.8 which is higher than the normal, and the distribution can then be described as leptokurtic.

For accuracy, a Jacque-Bera normality test was conducted which propose the following hypotheses:

$H_0$ : The variable is normally distributed

$H_1$ : The variable is not normally distributed

The Jarque-Bera statistic is given as follows:  $JB = \frac{n}{6} [S^2 + \frac{1}{4} (K - 3)^2]$

This statistic is compared to a Chi-square with a degree of freedom of 2. Or, the p-value of the Jarque-Bera is compared to the significance level  $\alpha$  which is usually 5%. The three return series have a p-value of 0 which is less than 5%; implying that the returns are not normally distributed. Moreover, the histogram plot <sup>2</sup> also supports the Jarque-Bera test by showing the non-normality of the distribution. Then  $\varepsilon_t$  can be modelled as t-distribution or GED distribution.

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<sup>2</sup> The histogram plots are available in the Appendix page.

In our models we will use the generalized error distribution (GED).

## 4.2 Diagnostic tests:

As seen in the return figures, the return series exhibit heteroskedastic characteristics.

We test for the existence of heteroscedasticity in the residuals with different tests.

**Table 3:**

	Breusch-Pagan- Godfrey	Harvey	Glejser	White	Arch (1 lag) <sup>3</sup>
<b>F</b>	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
<b>Probability</b>					

\*: significant at 10%    \*\*: significant at 5%    \*\*\*: significant at 1%

The first four tests have the following hypothesis.

$H_0$ : errors are homoscedastic

$H_1$ : errors are heteroscedastic

We reject  $H_0$  in all the 5 tests and assume that the errors are heteroskedastic.

The last test which is Arch test have the following hypothesis.

$H_0$ : no Arch effect

$H_1$ : Arch effect exists

We reject  $H_0$  and an Arch effect exists in the return series.

Since errors are heteroskedastic and an arch effect exists, we can safely begin exploring GARCH models.

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<sup>3</sup> After testing the number of lags needed to complete the arch test, the q statistic was insignificant at the first lag.



In summary of the OLS model, we had some violations to the linear regression model properties, the errors are not normally distributed and the data is not linear and an arch effect exist. So we can safely use an ARCH/GARCH model in our approach. “Since the BDS test has reasonable power against the GARCH models, it has been used as a diagnostic tool to determine the adequacy of GARCH models for detecting non-linearity of the series” (Guglielmo, 2005). In this case, the standardized residuals from the fitted GARCH models are subjected to the BDS test under the null hypothesis of sufficient linear components of the series. If the BDS test do not rejects the null hypothesis, then the fitted GARCH model is assumed to be an adequate characterization of the data.

**Table 4: BDS independence test**

<b>BDS statistic/ [std. error]</b>	<b>ARCH (1)</b>	<b>GARCH (1, 1)</b>	<b>PARCH (1, 1)</b>	<b>EGARCH (1,1)</b>
<b>Dimension 2</b>	-0.004485*** [0.001238]	-0.000195 [0.001049]	-0.000488 [0.001025]	-0.000148 [0.001030]
<b>Dimension 3</b>	0.006883*** [0.001961]	0.001271 [0.001661]	0.000313 [0.001622]	0.001080 [0.001631]
<b>Dimension 4</b>	0.019881*** [0.002328]	0.002099 [0.001970]	0.000700 [0.001923]	0.001823 [0.001934]
<b>Dimension 5</b>	0.030552*** [0.002419]	0.003068 [0.002045]	0.001169 [0.001996]	0.002433 [0.002007]
<b>Dimension 6</b>	0.037183*** [0.002326]	0.003285 [0.001965]	0.001162 [0.001916]	0.002409 [0.001927]

\*: significant at 10%    \*\*: significant at 5%    \*\*\*: significant at 1%

As the results show, the test statistics for the BDS tests are not significant for GARCH (1,1), PARCH (1,1), and EGARCH (1,1) implying that we cannot reject the null hypothesis of the i.i.d. process for the series. This also confirms that the models that are fitted are suitable ones and we can be sure that the variations of the GARCH models that we used with the provided parameters and orders are providing a good explanation of the data. It does not mean that these are the “best” descriptive models on the data, but considering the time and skills limitations of the author, we are hopeful that this research provides a basis for the further future work on the topic and the related data.

### **4.3 EGARCH model:**

In a GARCH model, coefficients have to be positive. In order to avoid encountering this problem, and to account for asymmetries between positive and negative shocks, we will consider EGARCH (1, 1) model to estimate volatility. After executing the model and checking the mean and variance equation, we should check for autocorrelation and heteroscedasticity.

Table 5, 6, and 7 represents the EGARCH models for US, EU and Asia. The mentioned tables include Ljung-Box test to examine autocorrelation in the series, Ljung-Box squared test to examine heteroscedasticity, and ARMA terms. The standardized errors should not to be auto-correlated and the standardized error squared should not to be heteroscedastic.

Table 5: EGARCH US <sup>4</sup>

Variables	Model 1	Model 2	Model 3
<b>Mean equation</b>			
$\alpha$	0.018241** [0.009239]	0.027601*** [0.007678]	0.029664*** [0.007133]
EU return	0.350008*** [0.007137]	0.363089*** [0.007019]	0.364724*** [0.006989]
Asia return	-0.007748 [0.010984]	0.035689*** [0.010952]	0.045907*** [0.011009]
B.E.S.I	0.042604* [0.022154]	0.034788 [0.021652]	0.033862** [0.020525]
AR (1)	-	-0.222234*** [0.014181]	-
AR (2)	-	-0.073237*** [0.014544]	-
MA (1)	-	-	-0.229062*** [0.014519]
<b>Variance equation</b>			
$\gamma$	0.129645*** [0.011228]	-0.136635*** [0.011565]	-0.137893*** [0.011545]
$\left  \varepsilon_{t-1} / \sqrt{\sigma_{t-1}^2} \right $	0.150012*** [0.013682]	0.158202*** [0.014057]	0.159334*** [0.014045]
$\varepsilon_{t-1} / \sqrt{\sigma_{t-1}^2}$	-0.147300*** [0.010233]	-0.120704*** [0.009186]	-0.113178*** [0.008817]
$\ln(\sigma_{t-1}^2)$	0.977561*** [0.002758]	0.978599*** [0.002824]	0.978484*** [0.002833]
<b>Ljung - Box. (5)</b>			
<b>(P-values)</b>	146.13*** (0.000)	28.839*** (0.000)	6.8112 (0.146)
<b>Ljung - Box. ^2 (5)</b>			
<b>(P-values)</b>	14.871** (0.011)	10.781** (0.056)	10.884* (0.054)

<sup>4</sup> NB: [standard deviation]

**Table 6: EGARCH EU**

Variables	Model 1	Model 2	Model 3
<b>Mean equation</b>			
$\alpha$	-0.018837 [0.012403]	-0.010298 [0.009256]	-0.008698 [0.009094]
<b>US return</b>	0.591398*** [0.012613]	0.630533*** [0.012491]	0.631353*** [0.012499]
<b>Asia return</b>	0.339526*** [0.012899]	0.365870*** [0.012697]	0.366284*** [0.012647]
<b>B.E.S.I</b>	0.049273 [0.012403]	0.014494 [0.029932]	0.012706 [0.029563]
<b>AR (1)</b>	-	-0.245802*** [0.014100]	-
<b>AR (2)</b>	-	-0.078087*** [0.014486]	-
<b>AR (3)</b>	-	-0.037081*** [0.013916]	-
<b>MA (1)</b>	-	-	-0.253736*** [0.013624]
<b>Variance equation</b>			
$\gamma$	-0.128116*** [0.010116]	-0.126293*** [0.010007]	-0.127518*** [0.010020]
$\left  \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right $	0.168719*** [0.013198]	0.164615*** [0.013069]	0.166110*** [0.013088]
$\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}$	-0.074393*** [0.010290]	-0.048427*** [0.009140]	-0.047263*** [0.009093]
$\ln(\sigma_{t-1}^2)$	0.981027*** [0.003385]	0.983249*** [0.003267]	0.983008*** [0.003292]
<b>Ljung-Box (5)</b>			
<b>(P-values)</b>	197.8*** (0.000)	29.275** (0.048)	7.3667 (0.195)
<b>Ljung-Box ^2 (5)</b>			
<b>(P-values)</b>	12.942** (0.024)	8.4256 (0.134)	7.6855 (0.174)
<b>Akaike info citerion</b>			
<b>Schwarz citerion</b>	2.901535	2.853475	2.847648
<b>Hanna-Quinn citer.</b>			
<b>Log likelyhood</b>	-7150.538	-7029.524	-7016.572

<b>Table 7: EGARCH Asia</b>			
<b>Variables</b>	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
<b>Mean equation</b>			
$\alpha$	0.031352*** [0.010697]	0.034192*** [0.009920]	0.034519*** [0.009880]
<b>US return</b>	-0.044621*** [0.012373]	-0.022482* [0.012514]	-0.022720* [0.012520]
<b>EU return</b>	0.235029*** [0.009117]	0.244130*** [0.009199]	0.244003*** [0.009203]
<b>B.E.S.I</b>	0.015414 [0.033241]	0.017378 [0.031670]	0.017377* [0.031584]
<b>AR (1)</b>	-	-0.076208*** [0.014673]	-
<b>MA (1)</b>	-	-	-0.074990*** [0.014608]
<b>Variance equation</b>			
$\gamma$	-0.140773*** [0.012797]	-0.142970*** [0.012858]	-0.141654*** [0.012806]
$\left  \varepsilon_{t-1} / \sqrt{\sigma_{t-1}^2} \right $	0.169162*** [0.015766]	0.171694*** [0.015897]	0.170228*** [0.015825]
$\varepsilon_{t-1} / \sqrt{\sigma_{t-1}^2}$	-0.089959*** [0.009225]	-0.082530*** [0.008922]	-0.081697*** [0.008837]
$\ln(\sigma_{t-1}^2)$	0.971975*** [0.004108]	0.972137*** [0.004127]	0.972654*** [0.004093]
<b>Diagnostic tests</b>			
<b>Ljung-Box. (5)</b> <b>(P-values)</b>	14.778** (0.011)	4.7334 (0.449)	4.5362 (0.475)
<b>Ljung-Box. ^2 (5)</b> <b>(P-values)</b>	13.953** (0.016)	10.855* (0.054)	7.3667 (0.159)
<b>Information criteria</b>			
<b>Akaike info</b> <b>criterion</b>	2.525448	2.529122	2.525487
<b>Schwarz criterion</b>	2.538630	2.540983	2.538667
<b>Hanna-Quinn citer.</b>	2.530071	2.533282	2.530110
<b>Log likelyhood</b>	-6220.280	-6321.607	-6221.640

**Autocorrelation test:** $H_0$ : No autocorrelation in the errors $H_1$ : Autocorrelation exist in the errors**Heteroscedasticity test:** $H_0$ : errors are homoscedastic $H_1$ : errors are heteroscedastic**Model selection:**

First, we checked the autocorrelation and the heteroscedasticity of the standardized errors and the standardized errors squared respectively in table 5 EGARCH US. Model 3 was the only model that we failed to reject the null hypothesis for autocorrelation and heteroscedasticity. Model 3 is the best fit model for EGARCH US. Second, we checked the autocorrelation and the heteroscedasticity of the standardized errors and the standardized errors squared respectively in table 6 EGARCH EU. In both model 2 and 3, we failed to reject the null hypothesis for autocorrelation and heteroscedasticity, so to pick the best model, we compared the two models to observe which one minimizes the three criteria mentioned in the table and maximizes log likelihood, and model 3 was the best fit model for EGARCH EU. Third, we checked the autocorrelation and the heteroscedasticity of the standardized errors and the standardized errors squared respectively in table 7 EGARCH Asia. In both model 2 and 3, we failed to reject the null hypothesis for autocorrelation and heteroscedasticity, so to pick the best model, we compared the two models to observe which one minimizes the three criteria mentioned in the table and maximizes log likelihood, model 3 was the best fit model for EGARCH Asia.

#### 4.4 Three Stage Least Square method:

**Table 8: Three Stage Least Square system**

<i>Variables</i>	<i>Coefficient</i>	<i>Std. error</i>	<i>T-statistic</i>
$\omega_1$	0.005811	0.010444	0.556336
$\alpha_1$	0.946082***	0.014521	65.15351
$\beta_1$	0.536690	0.404595	1.326485
$\gamma_1$	-0.606050***	0.215721	-2.809411
$\theta_1$	-0.491463	0.381899	-1.286890
$\varphi_1$	0.585136***	0.201270	2.907216
$\omega_2$	0.013691**	0.006785	2.017765
$\alpha_2$	0.939728***	0.005254	178.8546
$\beta_2$	0.268803	0.167895	1.601020
$\gamma_2$	0.591449***	0.050064	11.81394
$\theta_2$	-0.227467	0.160148	-1.420354
$\varphi_2$	-0.558821***	0.049166	-11.36603
$\omega_3$	-0.016870	0.011468	-1.471031
$\alpha_3$	0.948800***	0.013212	71.81343
$\beta_3$	-0.683911***	0.229476	-2.980317
$\gamma_3$	1.536325***	0.128310	11.97354
$\theta_3$	0.610354***	0.220750	2.764908
$\varphi_3$	-1.439650***	0.123432	-11.66348

While using the three stage least square, we embedded the economic surprise announcement component (B.E.S.I) in the volatility and we have been able to produce the following results:

1. The US current volatility is affected by its own historical volatility. The US also exhibits volatility spillover towards the Asian market in terms of macroeconomic surprise announcements.
2. Volatility spillover between the US and EU stock markets return is not significant in terms of macroeconomic surprise announcement.
3. The EU current volatility is affected by its own historical volatility. The EU also exhibits volatility spillover towards the Asian market in terms of macroeconomic news announcements.
4. Asia's current volatility is affected by its own historical volatility. Furthermore, Asia exhibits volatility spillover towards the US and EU market in terms of macroeconomic news announcements.

The results are in line with other research and explain the linkages amongst the three markets. First of all, the results prove that the US is affected by its lag volatility. Brenner, Pasquariello, and Subrahmanyam (2009), claim that the arrival of surprise economic news has a statistically and economically significant impact on the US financial markets, but this impact varies greatly across asset classes. Stock return volatility decreases on the trading day before, increases on the day when the announcements are made, and subsequently decreases, which can explain the effect of US past volatilities on US current volatility. Moreover, the results showed that the US exhibit volatility spillover to Asian markets during surprise announcements. According to Dedi & Yavas (2017), the US is the main transmitter of volatility during period of crisis to developed and emerging markets (crises of 1987, 2000,



and 2008), which explains the volatility spillover witnessed in the results towards the Asian markets during macroeconomic surprise announcements.

Secondly, volatility spillover between the US and EU stock markets return is not significant in terms of macroeconomic news announcement. The US and EU are considered to be developed and efficient markets, so the investors are prone to react quickly to any market development (Jiang et al., 2012). Since we did not use intraday data in this study, one may explain the lack of significance for volatility spillover between the US and EU as investors reacting quickly to changes in the stock market and that the volatility dissipates quickly and do not linger on.

Thirdly, the results indicated that the EU is affected by its lag volatility, as well as exhibits volatility spillover toward the Asian market. Xiao & Dhesi (2010) claim that EU countries are interdependent among each other to some extent and there is no serious contagion effect between them to provoke volatility spill-over, in addition; both conditional and unconditional correlation reveals that European stock market are more dependent on each other. In addition, Kiyamz (2003), Lu & Lee (2007) found a high degree of correlation among European indices namely the DAX, CAC and FTSE with the Japanese Nikkei and the Chinese SSE composite index which supports the argument for transmission of volatility from EU to Asia's market during macroeconomic surprise announcements.

Finally, the results show that the Asian market experience volatility spillover toward EU and US in terms of macroeconomic surprise announcements. The Asian market sample chosen in this study is a mix of developed and emerging markets. Whereas the US and EU markets are

considered as developed and efficient markets, this may explain why during macroeconomic news announcements Asia's stock markets market experience an increase in volatility spillover. International investors tend to react quickly and close their short-term positions in Asia's stock markets and reinvest elsewhere, like in the US or EU, which can cause volatility to spillover from Asia to US and EU. This result is supported by many researchers, Patel and Sarkar (1998), Kodres and pritsker (2002), Lagunoff and Shreft (2001) confirm the often-held belief that correlations between US and emerging markets as well as EU and emerging markets tend to become higher during market decline.

#### 4.5 Findings Summary

**Ha<sub>0</sub>**: Stock markets are not interdependent and do not exhibit return volatility spillover.

**Ha<sub>1</sub>**: Stock markets are interdependent, and exhibit return volatility spillover.

**Table 9:**

<b>Ha<sub>0</sub>, / Ha<sub>1</sub></b>	<b>US</b>	<b>EU</b>	<b>Asia</b>
<b>US</b>	✓	✗	✓
<b>EU</b>	✗	✓	✓
<b>Asia</b>	✓	✓	✓

✓: we reject the null hypothesis

✗: failed to reject the null hypothesis

According to the results of the three stage least square approach and the EGARCH models, we can conclude that we reject the null hypothesis  $H_a$  except for EU and US. Stock markets are interdependent and exhibit volatility spillover except for EU and US.

**Hb<sub>0</sub>**: Economic news do not affect US, EU, and Asia's stock markets returns and volatility spillover.

**Hb<sub>1</sub>**: Economic news affect US, EU, and Asia's stock markets returns and volatility spillover.

**Table 10:**

<b>Hb<sub>0</sub> / Hb<sub>1</sub></b>	<b>US</b>	<b>EU</b>	<b>Asia</b>
<b>US</b>	✓	✗	✓
<b>EU</b>	✗	✓	✓
<b>Asia</b>	✓	✓	✓

✓: we reject the null hypothesis

✗: failed to reject the null hypothesis

According to the results of the three stage least square approach and the EGARCH models, we can conclude that we reject the null hypothesis  $H_b$  except for US and EU. Stock market exhibit return volatility spillover in terms of macroeconomic surprise announcements, with the exception of US and EU. Volatility spillover was not significant between US and EU in terms of macroeconomic news announcement.

## Chapter 5

### Conclusion

#### 5.1 Introduction

In this thesis, we studied the interdependence in terms of return volatility spillover among major stock markets, particularly US, EU and Asia. This thesis also tested the impact of news announcements on the instantaneous volatility of the aforementioned commodities. This study then applied several econometric techniques. After conducting cointegration test, we observed that there are no long-term relationships between any of the stock market indices. This finding can be attributed to the fact that there have not been any observable trends to establish long-term relationships between our chosen stock markets. This study, then uses ARMA-EGARCH to model volatilities. The properties of ARMA-EGARCH allow us to model the mean of the process as ARMA and the conditional variance of the process as EGARCH, which makes it a desirable model for the purpose of our study. Furthermore, its flexibility of not having to estimate so many parameters as the multivariate GARCH models is another motivation for its preference. Given the stability of the estimated ARMA-EGARCH model, we conclude that the obtained volatilities can be accurately employed. A system of three simultaneous equations was constructed to detect both the instantaneous and delayed volatility spillover among the sampled stock markets. The simultaneous equations model provided a significant bidirectional influence between the Western markets and Pacific Asia markets. More specifically, and as a result of macroeconomic news announcements, this thesis found that an increase in the volatility of the US stock market decreased the volatility of Asian stock market by 0.68%. However, an increase in the volatility of the EU stock market increased the volatility of Asian stock market by 0.61%. In addition, and due to the

impact of news announcements, an increase in the volatility of Asian stock market decreased US stock market volatility by 0.60% and increased EU stock market volatility by 0.59%. On the other hand, macroeconomic news announcements do not have any significant impact on the volatility spillover between US and EU stock markets.

## **5.2 Summary of the Chapters**

The first chapter in this study covered the introduction, purpose, and motivation of the study. In the second chapter, the study presented the theoretical background of the topic; which covered the concept and origin of several important financial theories such as the modern portfolio theory, market portfolio theory and international portfolio diversification theory. The second chapter also discussed the empirical part of the topic. It covered recent research regarding unidirectional and bidirectional volatility spillover among developed and developing countries during crisis periods as well as during calm periods. In addition, the empirical part demonstrates the recent literature and findings on the impact of news announcements on stock markets. This part concluded that there is no consensus among the very few studies that dealt with the impact of news announcements on volatility spillover. The third chapter in this study presented the methodology. It included the research questions and the hypothesis. It discussed the different econometric tests that can be used and concluded that the ARMA-EGARCH method is suitable for modelling volatilities. Furthermore, this chapter illustrated the use of simultaneous equation models, and the three stage least square system to test the significance impact of news announcements on the volatility spillover across the sample. The fourth chapter presented the findings of the study. The main findings showed that the macroeconomic news announcements affect US and Asia's stock market returns but does not affect EU stock market return. We then incorporated

the volatility in the three stage least square approach. The results indicated a significant volatility spillover between US/Asia and between EU/Asia. Moreover, the US and Asian stock markets exhibit bidirectional volatility spillover, and an increase in US volatility decreases the Asian market volatility, which suggests that a weak market linkage exist between the two markets. In addition, the EU and Asian stock markets also exhibit bidirectional volatility spillover but experience strong market linkage. These findings are online with other results from the literature such as Li (2012) and Gunasinghe (2005). However, results from this chapter showed that macroeconomic news announcements have no significant impact on the volatility spillover between the US and the EU stock returns.

Furthermore, the surprise news affects the US, the EU, and the Asia's stock market returns volatility differently. This is partly due to the nature and geography of these markets. The nature of the Asian market is attractive for international investors in terms of diversification, and attractiveness of returns. This is evident in the world investment report (2018), which states that Pacific Asia regained its position as the largest FDI stock recipient region, and its share in global FDI stock inflows rose from 25 percent in 2016 to 33 per cent in 2017. The largest three recipients were China, Hong Kong (China) and Singapore. In addition, our findings cannot confirm whether there is a weak or strong market linkage between EU and US stock markets. The results support the general notion of coupling for the three markets during the period of the study, which states that if there is an increase or decrease in the coupling during the surprise announcements, a strong or weak market linkage between the markets can be detected. In conclusion, these findings support the hypothesis that cross-market interactions and dependency are stronger during market downturns than market upturns since the macroeconomic surprise announcement component is heavily reliant on bad news rather than good news. Our results are in line with other research such as Li and Giles

(2013), where they claim that for both the long run and the short run, the emerging markets are more affected by their own past shocks, as compared to developed markets, moreover, their result indicates that emerging markets seem to be more affected by “good news”. Nevertheless, the researchers concluded that it does not matter which market is examined, because the negative effects are always stronger in the overall effect. These finding also show that the financial crises have led to diminishing interdependencies of the developed markets on each other, while raising significance of developed countries on emerging ones. The Three stage least square approach implies dependency of bi-directional nature between US and Asia stock markets, and between EU and Asia stock markets on the other hand. The results of our research suggest that macroeconomic news announcements have significant effect on the interdependencies among major stock markets in this study. In some instances, it led to diminishing interdependence, while in others it increased the ties between stock markets returns illustrated by the example between EU and Asia stock markets.

### **5.3 Managerial Implications**

The empirical findings of this study have important implications on portfolio diversification and risk management practices. With the recent globalization, investors worldwide are finding it easier to access funds, seek new investment opportunities and follow innovative hedging strategies. However, the results of this dissertation constitute a perfect proof that there is risk proliferation and volatility transmission among stock markets. In addition, Interdependence of developed and emerging stock markets is of great significance to fund managers, because strong stock markets linkage decreases the protection of the domestic market from any global shock and produces policy implications to the countries in question;

while weak market linkage provides potential gains from international diversification (Singh, Kumar & Pandey, 2008).

Accordingly, our findings have several implications for both investors and policy makers. Since we found no linkage between EU and US stock markets means that there is a possibility for diversification strategies between the two markets. Slimane et al. (2013) provided evidence of deep interdependence between European markets, which supports the idea of investing in the EU market for diversification and hedging strategies during periods of turmoil. Since volatilities can proxy for risk, there are lessons for both individual and institutional investors in terms of further examining pricing securities, hedging and other trading strategies as well as framing regulatory policies.

The results are also important for policymakers in the sampled countries for understanding the markets' co-movements and designing policies. These findings can also be relevant to Asian policy makers debating the advantages and disadvantages of increasing financial integration in the region, since the results suggests a weak market linkage with US and a strong one with EU. In such a financial context, becoming more and more integrated creates a great interest in identifying potential gains from international portfolio diversification, and hedging strategies. These results are important for investors since volatility helps them make profit, price and return volatilities are both beneficial for the investor. The results suggest that the Asian stock market is well suited for investors because Asian market is found to have a strong linkage with EU stock market and a weak market linkage with US stock market. In addition, and since the US stock market is the dominant market in which major financial events happen, then Asian stock market can be an alternative market for western investors and fund managers, to hedge, diversify and to search for arbitrage opportunities in strong



emerging markets. Whereas, EU and Asia's stock market relationship is strong, so an increase in return volatility in one market will spill over to the other, thus limiting the opportunity for hedging between these two markets.

#### **5.4 Limitations and further studies**

This thesis remains with some limitations, which nonetheless offer visions for future research. Given the relatively short time frame provided for the thesis preparation, the sample of markets studied was limited to 3 main stock markets, while excluding several stock markets such as the BRICS which could affect the relation among the studied group. Additionally, there are several other macroeconomic variables that were not accounted for as control variables, such as interest rate differentials among countries, exchange rate volatility, and oil prices due to the lack of available daily data. As for the methodology used in this thesis, there is one main limitation that could have affected our results which is related to the use of daily data instead of intraday data. By using intraday data, we may be able to better capture the impact of macroeconomic news announcements on the volatility spillover between EU and US stock markets.

The findings of this thesis and their implications on international portfolio diversification are of great importance, and thus deserve further exploration in future studies. One of the possible improvements for this thesis is to include other major stock markets such as the BRICS stock markets in the evaluation of return volatility spillover, given their increasingly important role in global trade, which make them a force to be reckoned. A careful examination of the effect of additional macroeconomic and market variables on stock markets' return volatility, such as interest rate differentials, and stock trading volume can

help identify the factors that can serve well as control variables in order to avoid result bias. Finally, future research could better explain the impact of news announcement on volatility spillover by using intraday data.

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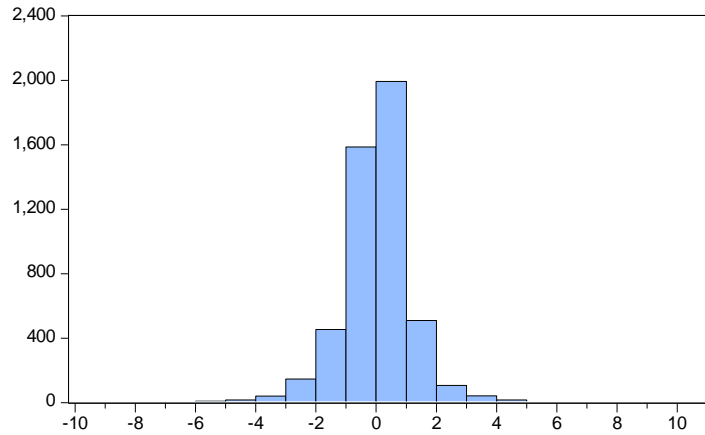
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## **APPENDIX**

### **LIST OF THE SURPRISE ANNOUNCEMENTS IN THE INDEX**

1. Wholesale Inventories MoM
2. Change in Nonfarm Payrolls
3. Change in Manufacturing Payrolls
4. Unemployment Rate
5. Consumer Credit
6. ADP Employment Change
7. ISM Non-Manufacturing Composite
8. Factory Orders
9. Wards Total Vehicle Sales
10. Wards Domestic Vehicle Sale
11. Personal Income
12. Personal Spending
13. ISM Manufacturing
14. Construction Spending MoM
15. ISM Milwaukee
16. Chicago Purchasing Manager
17. Pending Home Sales MoM
18. Durable Goods Orders
19. New Home Sales
20. Consumer Confidence Index
21. Richmond Fed Manufacturing Index
22. Dallas Fed Manufacturing activity
23. Existing Home Sales

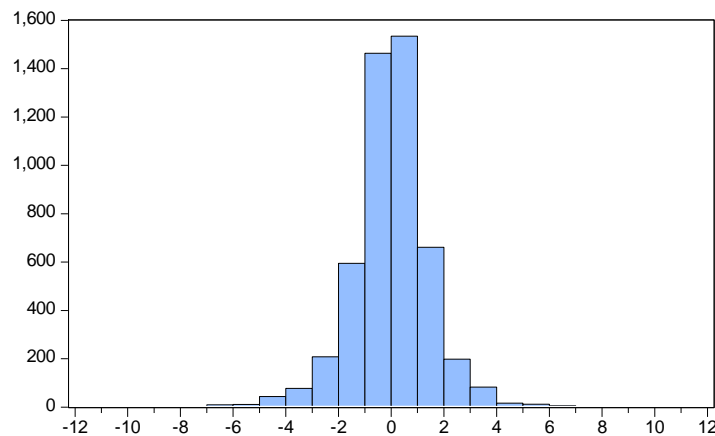
- 24.Industrial Production
- 25.Retail Sales
- 26.Capacity utilization
- 27.NAHB Housing Market
- 28.University of Michigan Sentiment
- 29.Building Permits
- 30.Leading Index
- 31.Empire Manufacturing
- 32.Initial Jobless Claim
- 33.Pending Home Sales
- 34.Continuing Claims
35. Consumer Price Index
- 36.Non-Farm Payroll
- 37.Building permits
- 38.Philadelphia Fed Manufacturing index
- 39.Target Federal Funds Rate

**Figure 2: Market Return Histogram****US Return Histogram:**

Series: RETURN\_US  
 Sample 1/03/2000 3/19/2019  
 Observations 4935

Mean 0.015201  
 Median 0.032519  
 Maximum 10.84037  
 Minimum -9.330356  
 Std. Dev. 1.189599  
 Skewness -0.238771  
 Kurtosis 11.20919

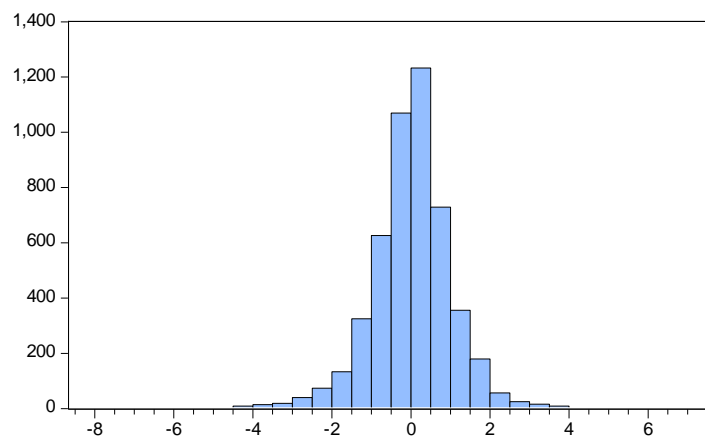
Jarque-Bera 13904.13  
 Probability 0.000000

**EU Return Histogram:**

Series: RETURN\_EU  
 Sample 1/03/2000 3/19/2019  
 Observations 4935

Mean -0.003477  
 Median 0.025322  
 Maximum 11.28545  
 Minimum -11.23508  
 Std. Dev. 1.533268  
 Skewness -0.114390  
 Kurtosis 8.850790

Jarque-Bera 7049.664  
 Probability 0.000000

**Asia's Return Histogram:**

Series: RETURN\_ASIA  
 Sample 1/03/2000 3/19/2019  
 Observations 4935











Mean 0.006666  
 Median 0.045020  
 Maximum 7.113481  
 Minimum -8.248173  
 Std. Dev. 1.057118  
 Skewness -0.587254  
 Kurtosis 8.109040

Jarque-Bera 5650.937  
 Probability 0.000000

**Figure 2: EGARCH USA, Ljung-Box Correlogram.**











**Model 1:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.169	-0.169	140.68	0.000
		2 -0.027	-0.057	144.29	0.000
		3 0.007	-0.007	144.57	0.000
		4 0.002	0.001	144.60	0.000
		5 -0.018	-0.017	146.13	0.000











**Model 2:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4934

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.021	-0.021	2.1065	0.147
		2 -0.071	-0.071	26.942	0.000
		3 0.000	-0.003	26.943	0.000
		4 0.001	-0.005	26.945	0.000
		5 -0.020	-0.020	28.839	0.000

**Model 3:**



Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.004	-0.004	0.0796	0.778
		2 -0.031	-0.031	4.8467	0.089
		3 -0.002	-0.002	4.8645	0.182
		4 -0.002	-0.003	4.8928	0.298
		5 -0.020	-0.020	6.8112	0.235

**Figure 3: EGARCH EU, Ljung-Box Correlogram.**



**Model 1:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.197	-0.197	191.27	0.000
		2 -0.019	-0.061	193.14	0.000
		3 -0.016	-0.033	194.34	0.000
		4 0.003	-0.009	194.38	0.000
		5 -0.026	-0.031	197.80	0.000



**Model 2:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4934

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.013	-0.013	0.7828	0.376
		2 -0.069	-0.069	24.312	0.000
		3 -0.022	-0.024	26.771	0.000
		4 -0.005	-0.011	26.913	0.000
		5 -0.022	-0.025	29.275	0.000

**Model 3:**











Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.007	0.007	0.2513	0.616
		2 -0.018	-0.018	1.7647	0.414
		3 -0.024	-0.023	4.5052	0.212
		4 -0.006	-0.006	4.6877	0.321
		5 -0.023	-0.024	7.3667	0.195













**Figure 4: EGARCH ASIA, Ljung-Box Correlogram.****Model 1:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.045	-0.045	10.116	0.001
		2 0.001	-0.001	10.123	0.006
		3 0.028	0.028	13.891	0.003
		4 -0.005	-0.003	14.038	0.007
		5 -0.012	-0.013	14.778	0.011











**Model 2:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4934

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.006	0.006	0.1996	0.655
		2 -0.004	-0.004	0.2818	0.869
		3 0.026	0.026	3.5112	0.319
		4 -0.004	-0.005	3.6053	0.462
		5 -0.015	-0.015	4.7334	0.449

**Model 3:**



Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.006	0.006	0.1701	0.680
		2 0.001	0.001	0.1758	0.916
		3 0.025	0.025	3.3705	0.338
		4 -0.005	-0.005	3.4728	0.482
		5 -0.015	-0.015	4.5362	0.475

**Figure 5: EGARCH USA Ljung-Box squared Correlogram.**



**Model 1:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.050	0.050	12.379	0.000
		2	0.014	0.011	13.292	0.001
		3	0.003	0.001	13.326	0.004
		4	0.011	0.011	13.952	0.007
		5	-0.014	-0.015	14.871	0.011



**Model 2:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4933

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.031	0.031	4.7127	0.030
		2	0.028	0.027	8.4889	0.014
		3	0.002	0.000	8.5118	0.037
		4	0.011	0.010	9.1325	0.058
		5	-0.018	-0.019	10.781	0.056

**Model 3:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.031	0.031	4.8609	0.027
		2	0.028	0.027	8.6214	0.013
		3	0.004	0.002	8.6932	0.034
		4	0.011	0.010	9.2539	0.055
		5	-0.018	-0.019	10.884	0.054

**Figure 6: EGARCH EU Ljung-Box squared Correlogram.****Model 1:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1	0.046	10.522	0.001
		2	0.006	10.715	0.005
		3	0.011	11.273	0.010
		4	0.010	11.812	0.019
		5	-0.015	12.942	0.024

**Model 2:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4932

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1	0.033	5.3943	0.020
		2	0.010	5.8475	0.054
		3	0.014	6.7647	0.080
		4	0.013	7.6637	0.105
		5	-0.012	8.4256	0.134

**Model 3:**



Date: 12/08/19 Time: 17:46  
Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1	0.031	4.7707	0.029
		2	0.008	5.0840	0.079
		3	0.014	5.9933	0.112
		4	0.014	6.9300	0.140
		5	-0.012	7.6855	0.174

**Figure 7: EGARCH Asia Ljung-Box squared Correlogram.**



**Model 1:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.008	-0.008	0.2853	0.593
		2 0.015	0.014	1.3307	0.514
		3 0.050	0.050	13.776	0.003
		4 -0.006	-0.005	13.951	0.007
		5 0.001	-0.001	13.953	0.016



**Model 2:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4934

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 -0.007	-0.007	0.2477	0.619
		2 0.018	0.018	1.7879	0.409
		3 0.043	0.043	10.728	0.013
		4 -0.005	-0.005	10.844	0.028
		5 0.001	-0.000	10.855	0.054

**Model 3:**

Sample: 1/03/2000 3/19/2019  
Included observations: 4935

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.007	0.007	0.2513	0.616
		2 -0.018	-0.018	1.7647	0.414
		3 -0.024	-0.023	4.5052	0.212
		4 -0.006	-0.006	4.6877	0.321
		5 -0.023	-0.024	7.3667	0.195

