<u>ISTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SOCIAL SCIENCES</u>

ANALYSIS OF VOLATILITY TRANSMISSION MECHANISM ACROSS EQUITY MARKETS

Ph.D. THESIS

Pınar KAYA

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ SOSYAL BİLİMLER ENSTİTÜSÜ

HİSSE SENEDİ PİYASALARINDA OYNAKLIK GEÇİŞLİLİĞİ MEKANİZMASININ ANALİZİ

DOKTORA TEZİ

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İktisat Anabilim Dalı

İktisat Programı

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HAZİRAN 2017

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Date of Submission : 2 May 2017

Date of Defense : 15 June 2017

This thesis is dedicated to my father Engin Kaya and my mother Berrin Kaya for their unconditional love, support and encouragement. Furthermore, I want to thank my brother Volkan Kaya for his support and love that helped me to be motivated throughout my life.

FOREWORD

I would like to express my gratitude to my supervisor Prof. Dr. Bülent Güloğlu, whose guidance, encouragement and insight made the accomplishment of this thesis possible.

This thesis has received a grant from TUBITAK under the project number 116K236 with the project title “Analyses of Risk Spillovers, Financial Contagion, Flight to Quality and Flight from the Quality among the Stock Exchange Markets of Turkey and the Developed and the Developing Countries by the Recent Developments in the Tail Dependence Measurement”.

A version of first essay has been published in “Physica A: Statistical Mechanics and its Applications” which is indexed in Science Citation Index-Expanded under the title of "Volatility Transmission among Latin American Stock Markets under Structural Breaks".

A version of second essay has been presented at International Conference on Applied Economics and Finance (ICOAEF 2016) Girne American University, Kyrenia, North Cyprus on 5-6 December with the title “Financial Contagion, Flight to Quality and Flight from the Quality among the Stock Exchange Markets of Turkey and the Developed and the Developing Countries”.

May 2017 Pınar KAYA

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ABBREVIATIONS

AEPD: Asymmetric Exponential Power Distribution
APARCH: Asymmetric Power Autoregressive Conditional Heteroskedasticity
AR: Autoregressive
ARCH: Autoregressive Conditional Heteroskedasticity
ARMA: Autoregressive Moving Average
BEKK: Baba-Engle-Kraft-Kroner,
CCC: Constant Conditional Correlation
DCC: Dynamic Conditional Correlation
EGARCH: Exponential Generalized Autoregressive Conditional Heteroscedasticity
Eq: Equation
FIAPARCH: fractionally integrated asymmetric power Autoregressive Conditional Heteroskedasticity
FIGARCH: Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity
GARCH: Generalized Autoregressive Conditional Heteroscedasticity
GOGARCH: Generalized Orthogonal Autoregressive Conditional Heteroscedasticity
GPH: Geweke and Porter-Hudak Model
GSP: Gaussian Semi Parametric
ICSS: Iterative Cumulative Sum of Squares
IGARCH: Integrated Generalized Autoregressive Conditional Heteroscedasticity
LA: Latin American
MEGARCH: Multivariate Exponential Generalized Autoregressive Conditionally Heteroscedastic
MGARCH: Multivariate Generalized Autoregressive Conditional Heteroscedasticity
PDF: Probability Density Function
QML: Gaussian Quasi Maximum Likelihood
R/S: Rescaled Range Statistics
VaR: Value at Risk
VAR: Vector Autoregression
VEC: Vector Error Correction
VIX: Volatility index
VMA: Vector Moving Average

SYMBOLS

$\mathbf{c_0}$ **:** Constant term

$\theta(.)$: p dimensional integral moment function.

δ : Power term parameter

$\mathbf{Y_{i,t-1}}$: Information set

$\boldsymbol{\varepsilon}_{\mathbf{t}}$: Residual of the mean equation

$\{\mathbf{y_{it}}\}$: Sequence of stationary continuous random variables

$\boldsymbol{\rho}_{\mathbf{i,j,t}}$ **:** Time-varying correlation coefficient

Ω **:** Variance covariance matrix

$\mathbf{C_k}$**:** Cumulative sum of squares of a series of uncorrelated random variables with mean 0 and variance σ^2

d: Fractional integration parameter

$\mathbf{D_k}$**:** Centered (normalized) cumulative sum of squares of a series of uncorrelated random variables with mean 0 and variance σ^2

$\mathbf{D_t}$**:** Diagonal matrix with time-varying standard deviations on the diagonal

$\mathbf{DU_{i,t}}$**:** Vector of dummy variables for country i at time t

H: Hurst exponent parameter

$\mathbf{h_t}$ **:** Conditional variance

$\mathbf{H_t}$**:** Conditional covariance matrix

i: Correspond to countries stock markets

IT: Inclan and Tiao statistics

j: Correspond to countries stock markets

k: Numbers of dummy variables corresponding to the phase of events

L: Lag operator

$\mathbf{P_t}$**:** Price of the asset at time t

$\mathbf{r_t}$: Return of the asset at time t

t: Time

x: Explanatory variables

z_{it}: Standardized residuals

γ : The asymmetric parameter

$\kappa 2$: kappa-2 statistics

Φ_i: Parameter space

φ_i: Parameter vector

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ANALYSIS OF VOLATILITY TRANSMISSION MECHANISM ACROSS EQUITY MARKETS

SUMMARY

This dissertation presents two studies on volatility transmission mechanism among developed and developing stock markets and U.S. bond market. The first essay investigates the volatility spillovers across developed and emerging stock markets by using dynamic conditional correlations. Throughout the first study to represent developed stock markets, S&P 500 (USA), FTSE-100 (UK), NIKKEI 225 (Japan) indices were used and emerging stock markets were represented by two regional groups. One of them is Asian stock markets namely BSE SENSEX Index (India), IDX (Indonesia), BURSA KLCI (Malaysia), and BIST 100 (Turkey). The other group consists of four major Latin American stock markets MERVAL (Argentina), BOVESPA (Brazil), IPC (Mexico), IPSA (Chile) and COLCAP (Colombia). In this study, spanning the period from 01/01/2002 to 29/02/2016, daily index values of these stock markets were analyzed. In this essay the presence of the structural breaks in variance, long memory property and asymmetry were taken into account. In order to test for long memory property, Rescaled Range Statistics (R/S), Geweke and Porter-Hudak (GPH) Model and Gaussian Semi Parametric (GSP) methods were employed. These test results confirmed that there exists long memory behavior in squared returns of all the stock indices. As a result, FIGARCH specifications seems to be an appropriate modelling framework. The findings also indicated that the relevance of significant asymmetry in the dynamics of stock returns, suggesting that volatility also depends on the sign of unexpected random shock. That is to say, FIAPARCH model allowing for asymmetry in the return and volatility series leads to better fitting. In this study, multivariate dynamic conditional correlation GARCH (DCC-GARCH), dynamic conditional correlation fractionally integrated GARCH (DCC-FIGARCH) and dynamic conditional correlation fractionally integrated asymmetric power autoregressive conditional heteroscedasticity (DCC-FIAPARCH) models were used. Finally, the dynamic conditional correlations were analyzed in order to interpret whether there is an increase in cross-market linkages after a shock or an interdependence across stock markets. Dealing with developed markets, it has been found that there exists higher integration between S&P 500 and FTSE 100. For these markets the correlations are above 0.5 suggesting higher integration between them. On the other hand, on average the correlations between NIKKEI 225 and other markets are less than 0.24. This result indicates that there is portfolio diversification opportunities between NIKKEI 225 and other developed markets. According to estimation results, the evidence has been found that Asian markets are weakly correlated. On average the correlations among Asian stock markets are less than 0.5, whereas the correlations between Malaysia and Indonesia are around 0.4. These results indicate that Asian markets are weakly correlated. Crisis dummies have a significant and positive impact on the dynamic conditional correlations between Asian stock markets, supporting the hypothesis of contagion effect. However, the picture is somewhat different for BOVESPA and MERVAL and BOVESPA and IPC. For these

markets the correlations are very high suggesting higher integration between them. The results suggested that diversification opportunities do not seem to exist between BOVESPA and MERVAL, and BOVESPA and IPC. In addition, global financial and Eurozone crisis have positive impact on the DCCs, implying that the exogenous shifts led to a rise in the volatility of the correlations between Latin American stock markets. This finding supports the hypothesis of the contagion effect.

In the second essay, the main purpose is to analyze the risk spillovers, "flight to quality" from stock to bond; "flight from quality" from bond to stock and "financial contagion" among the stock exchange and bond markets by using the recently developed econometric techniques. By using the Granger causality tests in moments the "contagion", "flight to quality" and "flight from quality" effects were investigated for BIST 100 (Turkey) and the other financial markets. These tests differ from the Granger causality tests in means and variances in describing the causality in the tails of the distribution and their risk spillovers. Thus it can be determined whether a negative shock to a market influences the other market positively or not. Throughout the study to represent regional stock markets; Standard and Poor's Europe Stock Market Index (SPEU), Standard and Poor's Asia Stock Market Index (SPAS 50) and S&P Africa 40 index were used. National stock markets were represented by BIST 100 (Turkey), S&P 500 (USA), DAX 100 (Germany), FTSE 100 (UK), NIKKEI 225 (Japan), MERVAL (Argentina), BOVESPA (Brazil), IPC (Mexico), IPSA (Chile), COLCAP (Colombia), IDX (Indonesia), S&P BSE SENSEX Index (India), and BURSA KLCI (Malaysia). In order to analyze flight to quality and flight from quality phenomena, causal relationship between these stock markets and U.S. bond market was investigated in this concept. In this study, spanning the period from 01/01/2002 to 29/02/2016 daily index values of these stock markets and the two year U.S. bond yield were analyzed. The results of this study are helpful for analyzing the sensitivity of the risks of the Turkish stock market relative to the other markets over time. They are also helpful to understand whether there is a flight to quality or contagion when the financial markets are exposed to a risk.

When stock markets were analyzed as regionally, it may be concluded that there exists a weak contagion from SPEU to BIST 100; a bilateral contagion between S&P Africa 40 and BIST 100; and strong interdependence between SPAS 50 and BIST 100. Furthermore, there exists negative contagion from S&P 500 and FTSE 100 to BIST 100. Moreover, there is a weak contagion from DAX 100 to BIST 100. However, the picture is different for the relationship between BIST 100 and NIKKEI 225. It can be stated that there is a weak volatility spillover from BIST 100 to NIKKEI 225 due to the causality in variance. But in the opposite direction, NIKKEI 225 has no influence on BIST 100. Therefore, one may suggest that NIKKEI 225 and DAX 100 are good diversification alternatives for investors investing in BIST 100.

By analyzing causality between BIST 100 and other emerging countries, the evidence shows that there exists negative contagion from IPC and MERVAL to BIST 100. Therewithal, it can be stated that BIST 100 is dependent on BOVESPA and IPSA by the reason of significant Granger causality in the center of the distributions. In addition, one way volatility spillover effect is observed from COLCAP to BIST 100. And for opposite direction, it can be seen that there is one way negative contagion from BIST 100 to IDX. Besides, there exist bilateral negative contagion between BIST 100 and SENSEX. Finally, there is bilateral volatility spillover between BIST 100 and MALAYSIA KLCI.

When the relationship between stock market and bond market was analyzed, having said that, there exists contagion from the U.S. bond market to the Japan stock market. The evidence shows that the London stock market index (FTSE 100), German stock market index (DAX 100), and U.S. stock market index (S&P 500) are dependent on the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when London stock index FTSE 100 is falling, U.S. two year bond yield (USGG2YR) is (weakly) negatively affected. Moreover, during bull market, when London stock index FTSE 100 is rising, U.S. two year bond yield (USGG2YR) is affected positively.

After all, one may conclude that BIST 100 is dependent on USGG2YR by the reason of significant Granger causality in the center of the distributions. According to test results, it can be seen that there exists negative contagion from USGG2YR to IDX, and SENSEX. In addition, there exists flight from quality effect from USGG2YR to SENSEX. It may be clarified that there exists weakly flight to quality from MERVAL to USGG2YR. It can be stated that Latin American markets such as IPC, IPSA, and BOVESPA are dependent on U.S. bond market. To sum up, one may conclude that KLCI and MERVAL are good diversification alternatives for USGG2YR.

HİSSE SENEDİ PİYASALARINDA OYNAKLIK GEÇİŞLİLİĞİ MEKANİZMASININ ANALİZİ

ÖZET

Bu tez gelişmiş ve gelişmekte olan hisse senedi piyasaları ve Amerika Birleşik Devletleri tahvil piyasaları arasında oynaklık geçişliliği mekanizması üzerine iki çalışmadan meydana gelmektedir. İlk makale dinamik koşullu korelasyonları kullanarak gelişmiş ve gelişmekte olan hisse senedi piyasaları arasında oynaklık yayılmalarını araştırmaktadır. İlk çalışmada gelişmiş borsa endekslerini temsilen S&P 500 (Amerika), FTSE 100 (Londra), NIKKEI 225 (Japonya) endeksleri kullanılmış olup gelişmekte olan ülkeler iki bölgesel grup tarafından temsil edilmiştir. Bu gruplardan ilki, BSE SENSEX (Hindistan), IDX (Endonezya), BURSA KLCI (Malezya) endekslerinin bulunduğu Asya borsaları ve BIST 100 (Türkiye) endeksinden oluşmaktadır. Diğer grup ise MERVAL (Arjantin), BOVESPA (Brezilya), IPC (Meksika), IPSA (Şili) ve COLCAP (Kolombiya)'nın bulunduğu beş temel Latin Amerika borsasını içermektedir. Bu çalışmada 01.01.2002 ile 29.02.2016 döneminde finansal piyasaların günlük endeks değerleri analiz edilmiştir. Bu çalışmada varyansta yapısal kırılma, uzun hafıza özelliği ve asimetri dikkate alınmıştır. Uzun hafızayı test etmek için Rescaled Range İstatistiği (R/S), Geweke ve Porter-Hudak (GPH) modeli ve Gaussian Semi Parametric (GSP) yöntemine başvurulmuştur. Test sonuçları tüm hisse endeksleri için getiri karelerinde uzun hafıza davranışını doğrulamaktadır. Bu nedenle FIGARCH analizinin bu yaklaşımı modellemede daha uygun olduğu saptanmıştır. Sonuçlar ayrıca dinamik endeks getirilerinde anlamlı bir asimetrinin varlığına işaret etmektedir, bu da oynaklığın, beklenmeyen rassal şokların işaretine bağlı olduğunu göstermektedir. Bu demek oluyor ki, getiri ve oynaklık serilerinde asimetriye izin veren FIAPARCH modeli bu durumda kullanıma daha elverişlidir. Çok değişkenli dinamik koşullu korelasyon GARCH (DCC-GARCH), dinamik koşullu korelasyon kısmi entegre edilmiş GARCH (DCC-FIGARCH) ve dinamik koşullu korelasyon kısmi entegre edilmiş asimetrik üssel otoregresif koşullu değişen varyans (DCC-FIAPARCH) modelleri kullanılmıştır. Son olarak bir şok sonrası çapraz piyasa korelasyonlarında bir artış olup olmadığını veya piyasalar arası karşılıklı bağlılık olup olmadığını yorumlayabilmek için dinamik koşullu korelasyonlar analiz edilmektedir. Gelişmiş piyasalar ele alındığında, S&P 500 ve FTSE 100 arasında yüksek bir bütünleşme olduğu gözlemlenmiştir. Bu piyasalar için korelasyonlar 0,5'in üzerindedir. Bu da aralarındaki yüksek entegrasyona işaret etmektedir. Diğer yandan, ortalama olarak NIKKEI 225 ve diğer gelişmiş piyasalar arasındaki korelasyonlar 0.24'ün altındadır. Bu sonuçlar NIKKEI 225 ve diğer piyasalar arasında portföy çeşitlendirme imkanlarının bulunduğuna işaret etmektedir.

Tahmin sonuçlarına göre Asya piyasaları arasında zayıf korelasyon bulunmaktadır. Ortalama olarak Asya borsaları arasındaki korelasyonlar 0,5' in altındayken, bu değer Malezya ve Hindistan arasında yaklaşık 0,4 civarındadır. Kriz kukla değişkenlerinin, Asya borsaları arasındaki dinamik koşullu korelasyonlar üzerinde pozitif ve anlamlı bir etkiye sahip olması bulaşma etkisi hipotezini destekler niteliktedir. Buna karşın BOVESPA, MERVAL ve BOVESPA, IPC için durum biraz farklı gözükmektedir. Bu

piyasalar arasındaki yüksek korelasyonlar, aralarındaki yüksek entegrasyonu göstermektedir. Bu sonuçlar BOVESPA, MERVAL ve BOVESPA, IPC arasında çeşitlendirme olanaklarının olmadığını öne sürmektedir.

Buna ek olarak, küresel finansal kriz ve Avrupa bölgesi borç krizi DKK'lar üzerinde pozitif bir etkiye sahiptir. Bu durum, dışsal etkilerin Latin Amerika piyasaları arasındaki korelasyonların oynaklığında artışa neden olduğunu göstermektedir. Bu bulgular, bulaşma etkisi hipotezini desteklemektedir.

İkinci makalede temel amaç kuyruk bağımlılığı ölçümündeki yeni ekonometrik tekniklerden yararlanarak gelişmiş ve gelişmekte olan hisse senedi borsaları arasında risk yayılımını incelemek, hisse senedi piyasalarından tahvil piyasalarına kaliteye kaçış, tahvil piyasalarından hisse senedi piyasalarına kaliteden kaçış ve hisse senedi ve tahvil piyasaları arasındaki finansal bulaşma olgularını ortaya çıkarmaktır. Bu çalışmada Türkiye ile bölgesel ve ulusal piyasalar arasında "bulaşma" ve "kaliteye kaçış" durumları araştırılmaktadır. Momentlerdeki Granger nedensellik testleri, ortalama ve varyanstaki Granger nedensellik testlerinden farklı olarak, dağılımın kuyruklarındaki nedenselliği ifade etmekte ve bu da riskteki yayılmayı göstermesi bakımından önem arz etmektedir. Böylece bir piyasanın maruz kaldığı negatif şokun, diğer bir piyasayı olumlu yönde etkileyip etkilemediği anlaşılabilmektedir. Çalışmada bölgesel düzeyde hisse senedi piyasaları için S&P Avrupa endeksi (SPEU), S&P Asya endeksi (SPAS 50) ve S&P Afrika endeksi (S&P Afrika 40) kullanılmıştır. Ulusal düzeyde hisse senedi piyasaları içinse BIST 100 (Türkiye), S&P 500 (ABD), DAX-100 (Almanya), FTSE 100 (İngiltere), NIKKEI 225 (Japonya), MERVAL (Arjantin), BOVESPA (Brezilya), IPC (Meksika), IPSA (Şili), COLCAP (Kolombiya), IDX (Endonezya), S&P BSE SENSEX (Hindistan) ve BURSA KLCI (Malezya) endeksleri kullanılmıştır. Bu bağlamda kaliteye kaçış ve kaliteden kaçış olgularını analiz etmek için bu borsalar ve ABD tahvil piyasası arasındaki nedensellik ilişkisi araştırılmaktadır. Bu çalışmada 01.01.2002 ile 29.02.2016 döneminde hisse senedi piyasalarının ve iki yıllık Amerikan tahvil getirisinin günlük endeks değerleri analiz edilmiştir. Çalışmadan elde edilecek sonuçlar yardımıyla Türkiye'deki hisse senedi piyasasının diğer piyasalara göre risklerinin zaman içinde nasıl değiştiği görülebilmektedir. Ayrıca elde edilen sonuçlar, finansal piyasaların riske maruz kalmaları durumunda, piyasalar arasında kaliteye kaçış mı yoksa finansal bulaşma mı olduğunu anlamaya yardımcı olmaktadır.

Hisse senetleri piyasası bölgesel olarak incelendiğinde, SPEU'dan BIST 100'e zayıf bir bulaşma, S&P Afrika 40 ile BIST 100 arasında çift yönlü bulaşma ve SPAS 50 ile BIST 100 arasında ise güçlü bir karşılıklı bağımlılık olduğu sonucuna varılabilir. Üstelik S&P 500 ve FTSE 100'den BIST 100'e negatif bulaşma vardır. Buna ek olarak, DAX 100'den BIST 100'e zayıf bir bulaşma vardır. Diğer yandan, BIST 100 ve NIKKEI 225 arasındaki ilişki farklı gözükmektedir. Varyanslardaki nedensellik nedeniyle, BIST 100' den NIKKEI 225'e zayıf bir oynaklık yayılması olduğu belirtilebilir. Fakat diğer taraftan, NIKKEI 225'in BIST 100 üzerinde herhangi bir etkisi yoktur. Bu nedenle, BIST 100'e yatırım yapan yatırımcılar için NIKKEI 225 ve DAX 100'ün iyi portföy çeşitlendirme alternatifleri olduğu söylenebilir.

BIST 100 ve diğer gelişen ekonomiler arasındaki nedensellik incelendiğinde, IPC ve MERVAL' dan BIST 100'e negatif bulaşma olduğu sonucuna ulaşılmaktadır. Aynı zamanda, dağılımların merkezindeki Granger nedenselliğinden dolayı, BIST 100'ün BOVESPA ve IPSA'ya bağımlı olduğu söylenebilir. Buna ek olarak, COLCAP'dan BIST 100'e tek yönlü oynaklık geçişliliği gözlemlenmektedir. Ve diğer taraftan, BIST 100'den IDX'e tek yönlü negatif bulaşma görülmektedir. Ayrıca, BIST 100 ve

SENSEX arasında çift yönlü negatif bulaşma vardır. Son olarak, BIST 100 ve MALAYSIA KLCI arasında çift yönlü oynaklık geçişliliği vardır.

Hisse senetleri ve Amerikan tahvil piyasası arasındaki ilişki incelendiğinde, belirtmek gerekir ki, Amerikan tahvil piyasasından Japonya borsasına bulaşma saptanmıştır. Bulgular gösteriyor ki FTSE 100, DAX 100 ve S&P 500 endeksleri Amerikan tahvil piyasasına bağımlıdır. Sonuç olarak sadece ayı piyasasında Londra borsası FTSE 100 düşüşte iken, iki yıllık Amerikan tahvil getirisi (USGG2YR) bu durumdan olumsuz fakat zayıf etkilenmektedir. Daha da ötesi, boğa piyasası sırasında, Londra borsası FTSE 100 yükselirken, iki yıllık Amerikan tahvil getirisi (USGG2YR) bu durumdan olumlu etkilenmektedir.

Sonuç olarak, dağılımların merkezlerinde anlamlı bir Granger nedenselliği söz konusu olduğundan, BIST 100'ün USGG2YR'e bağımlı olduğu sonucuna varılabilir. Test sonuçlarına göre USGG2YR'den IDX ve SENSEX'e negatif bulaşma olduğu gözlemlenmektedir. Buna ek olarak, USGG2YR'den SENSEX'e kaliteden kaçış etkisi gözlemlenmektedir. MERVAL'dan USGG2YR'e zayıf kaliteye kaçış etkisi olduğu açıklıkla ifade edilebilir. IPC, IPSA ve BOVESPA gibi Latin Amerika borsalarının Amerikan tahvil piyasasına bağımlı olduğu ortaya çıkartılmıştır. Özetlersek, MALAYSIA KLCI ve MERVAL, USGG2YR için iyi birer portföy çeşitlendirme alternatifi olabilir.

1. INTRODUCTION

1.1 Purpose of the Thesis

This thesis presents two separate but interrelated empirical researches on volatility transmission mechanism and risk spillovers across equity markets and U.S. bond market. The first essay investigates the volatility spillovers across developed and emerging stock markets by using dynamic conditional correlations. In the second essay, the main purpose is to analyze the risk spillovers, “flight to quality” from stock to bond; “flight from quality” from bond to stock and “financial contagion” among the stock exchange and bond markets by using the recently developed econometric techniques.

Volatility and correlation are two important metrics, which are used to measure the risk of investments in financial assets. As argued by Alexander (2008) the volatility of financial asset returns changes over time and this has an important inferences for risk measurement. Therefore, volatility is a fundamental issue in financial economics.

The notion of volatility transmission gains meaning with information flows (Chan et al, 1991). In this respect, an interesting question arises as how information or volatility in one market may spill over into other markets. Transmission mechanism comes into prominence for asset pricing, risk management and portfolio diversification, and for market efficiency.

There exist two approaches to test contagion and flight to quality. One of them is dynamic conditional correlations based on multivariate GARCH models and the other is causality tests. The empirically literature shows that if cross correlations between markets increase during crises period, there exists contagion between these markets. Moreover, correlation between two markets does not report the direction of the contagion. Hence, Granger causality approach is more appropriate to measure spillovers. In this thesis these two approaches are taken into account that complete each other.

In the light of recent and still growing literature of financial integration across countries and assets, the first essay investigates whether there exist volatility spillovers among stock markets in developed and emerging countries and attempts to identify the structure of the time varying correlations between stock markets.

The variation of market linkages between low market volatility (tranquil) regime and the high market volatility (turmoil) regime become more of an issue for calculating better hedge ratios and portfolio weights (Khalifa et al, 2012). Therefore, the primary objective of this study is to provide accurate estimation of risk measures, successful implementation of hedging strategies and assess the investment policies.

The second essay examines whether there is a possibility of risk diversification among financial markets by determining the causal relations especially between the tails of financial asset return distributions with the help of Granger causality analysis. And this study classifies the risk spillovers between Turkey and the other stock markets and also between stock markets and U.S. bond market as “financial contagion”, “flight to quality”, and “flight from quality”.

Flight to quality arises when correlation between stocks and bonds decrease in the period of falling stock markets. In contrast, increasing correlation between stock markets are described as a contagion in a crisis period. Flight from quality from bonds to stocks occurs if correlations between stocks and bonds decrease in rising stock markets. After financial distress, investors often reconstitute their portfolio from safe assets (bonds) to riskier assets (stocks). This rebalance is named as a flight from quality (Cheng and Yang, 2017).

According to Baur and Lucey (2009)’s analysis, there exist different types of relationships between stock and bond markets as in the Table 1.1,

Table 1.1 : Overview flight-to-quality, flight-from-quality and contagion.

	Stock-Bond Correlations are falling	**Stock-Bond Correlations are rising**
Stock Markets Falling	Stock-to-Bond Flight-to-quality	(Negative) Contagion
Stock Markets Rising	Bond-to-Stock Flight-*from*-quality	(Positive) Contagion
Bond Markets Falling	Bond-to-Stock Flight-*from*-quality	(Negative) Contagion
Bond Markets Rising	Stock-to-Bond Flight-to-quality	(Positive) Contagion

In this respect the aim of this essay is to examine the mechanisms of market risks spillovers. Throughout the study to represent regional stock markets; Standard and Poor's Europe Stock Market Index (SPEU), Standard and Poor's Asia Stock Market Index (SPAS50) and S&P Africa 40 Index and to represent developed stock markets; S&P 500 (USA), DAX 100 (Germany), FTSE 100 (UK), and NIKKEI 225 (Japan) are used and developing stock markets are represented by two regional groups. One of them is Asian stock markets namely BSE SENSEX Index (India), IDX (Indonesia), BURSA KLCI (Malaysia) and BIST 100 (Turkey). The other group consists of four major Latin American stock markets MERVAL (Argentina), BOVESPA (Brazil), IPC (Mexico), IPSA (Chile), and COLCAP (Colombia). And two year U.S. government bond (USGG2YR) returns are analyzed in this concept. In this study, daily index values of stock markets and bond market spanning the period from 01/01/2002 to 29/02/2016 are analyzed.

The latest developments in financial econometrics are used to achieve the goals and the objectives of this study. In this context, causality tests in moments developed by Chen (2016), which allow Granger causality tests not only in mean and variance but also in tail of the distributions, are used. In particular, the tests of causality between the tails of the distribution are important in the sense of showing the risk spillovers. The causality from the left tail of a given equity index distribution to the right tail of bond return distribution points to the flight to quality, while the causality between the left tails of the stock returns indicates the contagion effect. Finally, causality from the left tail of bond return distribution to the right tail of stock return distribution may be interpreted as flight from quality effect. Therefore, by means of Granger causality tests risk spillovers across markets are categorized as contagion, flight to quality and flight from quality.

2. DYNAMIC CONDITIONAL CORRELATION ANALYSIS OF VOLATILITY TRANSMISSION AMONG STOCK MARKETS IN THE PRESENCE OF STRUCTURAL BREAKS, ASYMMETRY AND LONG MEMORY

2.1 Introduction

Analyzing volatility spillover mechanism and correlations between markets can be useful for the pricing of securities, developing trading strategies, hedging strategies, and regulatory strategies within, and across the markets (Brailsford, 1996; Theodossiou et al, 1997). In order to adopt this important approach, dynamic conditional correlations are obtained from multivariate GARCH models of financial asset returns which are widely used in the literature.

Among several multivariate GARCH models, DCC-GARCH, DCC-FIAPARCH and DCC-FIGARCH models were used in this essay. As explained below, DCC-GARCH model was originally developed by Engle (2002), and it was extended to include the asset-specific correlation of news impact curves and the asymmetric dynamics in correlation by Cappiello et al. (2006). While investigating volatility transmission mechanism, long memory property and asymmetry effect are taken into account. The empirical applicability of long memory is familiarized by long memory models came to be known with their autocovariances falling into decay slowly. Pioneered by Ding et al. (1993) and Ding and Granger (1996), long memory conditional heteroscedasticity models have become widespread in the econometrics literature. According to Ding et al. (1993) fully decaying of a shock can last for long. The FIAPARCH model consists of the FIGARCH formulation of Baillie et al. (1996) with the APARCH model of Ding et al. (1993). Tse (1998) proposed FIAPARCH model which allows persistence (long memory) and asymmetry effects in the conditional volatility.

Most of the researchers put emphasis on the importance of considering structural breaks in testing for integration among the financial markets. It has been revealed that the existence of structural breaks in the unconditional variance of the series lead to the overestimation of the size of the GARCH parameters. Many of the recent studies employed Hong's (2001) test by allowing for the effects of structural breaks in the variance of the series, such as Korkmaz et al. (2012). In order to detect structural breaks in the unconditional variance of a stochastic process, they used a test procedure based on "Iterative Cumulative Sum of Squares" (ICSS) which was developed by Inclan and Tiao (1994):

$$IT = \sqrt{T/2D_k} \tag{2.1}$$

where $D_k = (C_k / C_T) - (k/T)$ and $C_k = \sum_{t=1}^{k} r_t^2$ be the cumulative sum of squares of a series of uncorrelated random variables with mean 0 and variance σ^2, for $t = 1, 2, \ldots, T$. The value of k $(k = 1, \ \ldots, \ T)$ that maximizes $\left| IT = \sqrt{T/2D_k} \right|$ is the estimate of the break date.

Under non-normality and in the presence of ARCH effects, the Kappa-2 (κ2) statistic developed by Sanso et al. (2004) is best suited in this context. For this reason, in this study, Kappa-2 test is carried out to examine the existence of structural breaks in variance before proceeding DCC-GARCH estimations.

In this essay, daily index values of stock exchange market indices of selected developing and developed countries spanning the period from 01/01/2002 to 29/02/2016 were analyzed. Throughout the study, to represent developed stock markets; S&P 500 (USA), FTSE 100 (UK), and NIKKEI 225 (Japan) were used. Emerging stock markets were represented by two regional groups. One of them is Asian stock markets namely BSE SENSEX Index (India), IDX (Indonesia), BURSA KLCI (Malaysia), and BIST 100 (Turkey). The other group consists of five major Latin American stock markets MERVAL (Argentina), BOVESPA (Brazil), IPC (Mexico), IPSA (Chile) and COLCAP (Colombia). In addition, COLCAP is the main stock market index of the Colombia Stock Exchange and was inaugurated on January 5th, 2008. Because of this, daily data of Latin American stock market was separated into two parts. The first part consists of daily index values of these five stock markets; MERVAL (Argentina), BOVESPA (Brazil), IPC (Chile), IPSA (Mexico), and COLCAP (Colombia) spanning the period from 16/01/2008 to 20/05/2015. And the other part contains only four of Latin American stock markets except COLCAP (Colombia) spanning the period from 01/01/2002 to 29/02/2016.

This chapter is structured as follows. Next section presents a literature review. In Section 2.3, basic time series features and descriptive statistics are covered. Section 2.4 discusses the most important empirical methodology, while Section 2.5 contains results on preliminary results of empirical modeling and testing for long memory process. Then, I summarize conclusions in Section 2.6.

2.2 Literature Review

Volatility and correlation are two important metrics which are used to measure the risk of investments in financial assets. It has been frequently observed that the volatility of financial asset returns changes over time and this has an important implications for risk measurement. Therefore, volatility has been a fundamental issue in financial economics ever since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle (1982). Autoregressive conditional heteroscedasticity (ARCH) models are used in a wide spread manner to describe and forecast changes in the volatility of financial time series. Bollerslev (1986) suggested an extended ARCH type model by adding lagged conditional variances to the ARCH model. The GARCH class-models assumes that the market variance is based on both past conditional market variance and past market shocks (Bollerslev, 1986). Hence, Generalized Auto Regressive Conditional Heteroskedasticity GARCH (p, q) process is given by:

$$R_t = \alpha_0 + \sum\nolimits_{i=1}^{k} \beta_i X_i + \sum\nolimits_{j=1}^{h} \psi_j R_{t-j} + \varepsilon_t \tag{2.2}$$

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

$$h_t = \omega + \sum\nolimits_{i=1}^{p} \beta_i h_{t-i} + \sum\nolimits_{j=1}^{q} \alpha_i \varepsilon_{t-j}^2 \tag{2.3}$$

where $h_t = \sigma_t^2 \left| \Omega_{t-1} \right.$

The parameters in this model should satisfy $\omega > 0, \alpha > 0, \beta \geq 0$. ε_t represents residuals of the mean equation, R_t denotes the return of the asset at time t, and X 's are explanatory variables. Equation (2.2) is the mean equation while Equation (2.3) is the conditional variance. Note that the parameters of the GARCH model are restricted to be strictly non-negative in order to satisfy the positive variance condition. Therefore GARCH models give information about the magnitude of the shock but not about its sign. If the sum of the estimated coefficients α and β is close or equal to one then this process is called Integrated GARCH model (Franses and Dijk, 2003). Thus, IGARCH models is commonly referred to as unit-root GARCH models. Although the IGARCH model is not covariance-stationary, as shown by Nelson (1990) it may still be strictly stationary (Franses and Dijk, 2003). Commonly high frequency financial data follows a pattern that yield a sum of α_1 and β_1 close to 1, with α_1 small and β_1 large. Therefore, the effect of shocks on the conditional variance diminishes very slowly. Baillie et al. (1996) recommended the class of Fractionally Integrated GARCH (FIGARCH) models. These models allow to notice a slowly decaying volatility as well as to recognize the long memory and short memory characteristic of conditional variance (Chkili, et al., 2014). Fractionally integrated processes are different from both stationary and unit-root processes with their persistence and mean reverting features. Formally, the FIGARCH (1,d,1) can be defined with lag operator "L" as follows

$$h_t = \omega + \beta h_{t-1} + \left[1-\left(1-\beta L^{-1}\right)\left(1-\lambda L\right)\left(1-L\right)^d\right]\varepsilon_t^2 \tag{2.4}$$

where $\omega>0$, $\beta \prec 1$ and $\lambda<1$. The fractional integration parameter d reflects the degree of long memory or the persistence of shocks to conditional variance, and satisfies the condition $0 \le d \le 1$. If $0 < d < 1$, the model implies an intermediate range of persistence and especially the volatility shocks disperse only at a hyperbolic rate. The integration parameter d = 0 indicates that the model has a short memory and reduces to the GARCH (1,1) model. On the other hand, if d = 1, model transforms to IGARCH (1,1) whose variance process is no longer mean-reverting (Chkili, et al, 2014).

Tse (1998) proposed fractionally integrated asymmetric power (FIAPARCH) model which allows persistence (long memory) and asymmetry effects in the conditional volatility. FIAPARCH model takes the form as below:

$$h_t^{\delta/2} = \omega\left(1-\beta L\right)^{-1} + \left[1-\left(1-\beta L\right)^{-1}\left(1-\lambda L\right)\left(1-L\right)^d\right]\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^{\delta} \tag{2.5}$$

where $\omega \succ 0, \delta > 0, \beta \prec 1, and\, \lambda < 1$.

The asymmetric parameter γ satisfies the condition $-1 < \gamma < 1$. When $\gamma > 0$ indicates that negative shocks are more effective on volatility than positive shocks of equal dimension. From Equation (2.5) we can see the fractional integration parameter d, $0 \le d \le 1$, like FIGARCH model, and holds long memory property in the conditional variance process. When $\gamma = 0$ and $\delta = 2$, the FIAPARCH model degrades to the FIGARCH model and when $d = 0$, reduces to the APARCH model. Conrad et al. (2011) implied that a sufficient condition for the conditional variance h_t to be positive almost surely for all t is that $\gamma > -1$ and the parameter combination (λ, d, β) satisfies the inequality constraints contributed in Conrad and Haag (2006) and Conrad (2010).

Silvennoinnen and Terasvirta (2008) emphasized that by constructing multivariate GARCH (MGARCH) models understanding the comovements of financial returns is of great practical importance. In addition, multivariate GARCH models have been used to investigate spillover effects in studies of contagion.

According to Bauwens et al. (2006), multivariate GARCH models differentiate into three approaches. The first approach ensures direct generalizations of the univariate GARCH model of Bollerslev (1986) such as the VEC, BEKK and factor models, flexible MGARCH, Riskmetrics, Cholesky and full factor GARCH models. The second is interested in linear combinations of univariate GARCH models such as (generalized) orthogonal models (GOGARCH) and latent factor models. The third deals with nonlinear combinations of the univariate GARCH models such as the constant (CCC) and dynamic conditional correlation models (DCC), the general dynamic covariance model and copula-GARCH models.

The notion of volatility transmission has gained meaning with information flows (Chan et al, 1991). It is desired to be known how information or volatility in one market may spill over into other markets. Transmission mechanisms come into prominence for asset pricing, risk management and portfolio diversification, and for market efficiency. Previous studies on volatility have been widely focused on risk measurement and volatility spillovers.

Engle and Susmel (1993) explored whether the two different international stock markets are following the same volatility process by benefiting from the time varying nature of variances. They found that there are two groups of countries having similar volatility behavior. One group is composed of Belgium, Germany, Norway, and Sweden. The second group is composed of Australia, Hong Kong, and Singapore/Malaysia.

Hamao et al. (1990) examined the price and price volatility dependence among the three main international stock markets. They have worked with daily opening and closing data of stock markets in Tokyo, London and New York. In their studies, they used ARCH-type models to examine the relationship between prices and have identified the existence of price volatility from New York to Tokyo, from London to Tokyo and from New York to London.

Long-memory property can be occurred in volatility of financial returns as well which points out wide-distant correlation of time-varying volatility elements. In his study, Robinson (1991) came up with the linear autoregressive conditional heteroskedastic model (LARCH) which permit long memory in the conditional variance. Later extensions of generalized ARCH (GARCH)-type models which take into account long-memory behavior have been proposed by many researchers. Baillie et al. (1996) constituted the fractionally integrated GARCH (FIGARCH) model which has been demonstrated to be convenient for this type of data in various empirical analyses (Bollerslev and Mikkelsen, 1996; Beine and Laurent 2003; Conrad and Karanasos 2005a; Conrad and Karanasos, 2005b).

Choudhry (1997) investigated the long-run relationship between the stock indices of six Latin American countries and the United States. He conducted unit root tests, cointegration tests, and error-correction models and his results supported the presence of a long-run relationship between the six Latin American indices (with and without the United States index) and significant causality among these indices.

In their study, Christofi and Pericli (1999) examined the systematic relationships between the five Latin American stock markets of Argentina, Brazil, Chile, Colombia and Mexico. Using a VAR and Exponential GARCH model, they showed the existence of asymmetric transmission of volatility innovations.

Using cointegration analysis and error correction vector autoregressions (VAR) techniques, Chen et al. (2002) analyzed the dynamic interdependence of the six stock markets in Latin America. They suggested that these countries' national stock price indices move together in the long-term. They further stated that investing in various Latin American stock markets offers limited risk diversification up until 1999. However, they found the evidence that for the period of 1999 to June 2000 creating a portfolio from shares in different Latin American countries reduces portfolio risk compared to a portfolio made up of shares from a single country.

Chiang et al. (2007) used a dynamic conditional-correlation model in order to investigate nine Asian daily stock-return data series from 1990 to 2003. By analyzing the correlation-coefficient series, they found contagion effect and a shift in variance during the crisis period. They suggested that international sovereign credit-rating agencies play a significant role in shaping the structure of dynamic correlations in the Asian markets.

Morales (2008) investigated the volatility spillovers between stock returns and exchange rate changes for six Latin American financial markets including Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela and Spain. He focused on the impact of the Euro in these markets. His results indicated that the volatility of stock prices affects the volatility of exchange rates; however, there is no evidence of volatility transmission in the opposite direction.

Verma and Ozuna (2008) examined price and volatility spillovers and response asymmetries between the equity markets of the United States and Brazil, Chile and Mexico. They employed multivariate exponential generalized autoregressive conditionally heteroscedastic (M-EGARCH) model. They provided the evidence that there are price and volatility spillovers from the United States to Mexico and Chile and but not to Brazil. They contended that openness of the country in terms of international trade plays crucial role for the spillovers.

Rivas et al. (2008) analyzed the volatility spillovers between European equity markets and the equity markets of Mexico, Brazil, and Chile. Reviewing the results of the E-GARCH and VAR models, Rivas et al. (2008) concluded that the stock markets of Spain and Germany have stronger volatility spillover effects on Latin American markets than do Italy, the United Kingdom, and France. They further stated that these spillover effects of Spain and Germany have a greater impact on Mexico and Brazil than on Chile. They asserted that the more open the economies are the more likely they are affected by external shocks. Considering asymmetry, they provided evidence that negative innovations raise volatility more than positive innovations.

Diamandis (2009) investigated long-run relationships between four Latin American stock markets and that of the US. He employed the autoregressive and moving average representations of a VAR model. The analysis suggested that there is a long-run relationship among the five equity markets.

El Hedi et al. (2010) analyzed the time variations in the comovements of Latin American stock markets. Employing time-varying correlations from a multivariate DCC-GARCH (Dynamic Conditional Correlation GARCH) model they estimated conditional correlations. They tested for structural breaks in the comovements with Bai and Perron's (2003) structural break technique. Their results indicated that the comovements are subjected to various regime shifts, essentially due to major economic events. They asserted that stock markets move much more together in times of crisis.

Aloui (2011) examined the volatility spillovers in Latin American emerging stock markets namely Argentina, Brazil, Chile and Mexico for the period (January 1995–September 2009). Using a multivariate Fractionally Integrated Asymmetric Power ARCH model with dynamic conditional correlations of Engle (1982) with a Student-t distribution he provided strong evidence of long memory and asymmetry in emerging stock market dynamics which offers an insight into the transmission of volatility shocks. Moreover, the pairwise DCCs' impulse response functions brought out that the Latin American emerging stock markets are interrelated in terms of risk transmission.

Lahrech and Sylwester (2011) investigated integration between Latin American equity markets and the US equity market. Using a DCC multivariate GARCH model they found the dynamic conditional correlation (DCC) between each market and that of the U.S. And as expected, they found a higher degree of co-movement between Latin Amarican countries' equity returns and those in the U.S.

Creti et al. (2013) investigated the links between price returns for 25 commodities and stocks over the period from January 2001 to November 2011. Using the dynamic conditional correlation (DCC) GARCH methodology, they showed that the correlations between commodity and stock markets are highly volatile especially since the 2007–2008 financial crisis and vary through time.

In their paper, Adrangi et al. (2014) employed an asymmetric bivariate EGARCH model in order to investigate the daily volatility spillovers between Standard and Poor's 500, and equity indices of Brazil, Argentina, and Mexico for the period from August 2007 through August 2012. They provided evidence of bi-directional spillovers. They further stated that the shock transmissions are asymmetric and there is a leverage effect. The authors reported that the causality runs in both directions, i.e., there is a shock feedback between markets. Finally, they found that equity market downturns in the US may have serious effects on the equity markets and economies of Latin America.

In their research, for the period of 2000 to 2013, Kang et al. (2016) found evidence that significant asymmetry and long memory volatility properties and DCCs for pairs of BRICS stock and commodity markets, and variability in DCCs and Markov Switching regimes during economic and financial crises.

2.3 Data

In this essay, spanning the period from 01/01/2002 to 29/02/2016, daily index values of stock market indices of selected emerging and developed countries were analyzed. Throughout the study to represent developed stock markets; S&P 500 (USA), FTSE-100 (UK), and NIKKEI 225 (Japan) were used and developing stock markets were represented by two regional groups. One of them is Asian stock markets namely BSE SENSEX Index (India), IDX (Indonesia), BURSA KLCI (Malaysia), and BIST 100 (Turkey). The other group consists of five major Latin American stock markets MERVAL (Argentina), BOVESPA (Brazil), IPC (Mexico), IPSA (Chile) and COLCAP (Colombia). In addition, COLCAP is the main stock market index of the Colombia Stock Exchange and was inaugurated on January 5th, 2008. Because of this, daily data of Latin American stock markets was separated into two parts. The first part consists of daily index values of these five stock markets; MERVAL (Argentina), BOVESPA (Brazil), IPC (Chile), IPSA (Mexico), and COLCAP (Colombia) spanning the period from 16/01/2008 to 20/05/2015. And the other part contains only four of Latin American stock markets except COLCAP (Colombia) spanning the period from 01/01/2002 to 29/02/2016. The data set was extracted from the DataStream International (Thomson Financial). Daily returns are calculated as log differences of price levels as follows:

$$r_t = 100 \times \left[\ln P_{i,t} - \ln P_{i,t-1} \right] \tag{2.6}$$

Descriptive statistics for return series are presented in Tables 2.1-2.4. As can be seen from tables, stock market returns have excess kurtosis (fat tails) and negative skewness. Moreover, the Ljung-Box Q and Q^2 statistics are highly significant.

Furthermore, ARCH tests are highly significant indicating the presence of ARCH effects. This justifies the use of ARCH-type modeling techniques.

Table 2.1 : Descriptive statistics of developed stock market return series.

	SP_500	**FTSE_100**	**NIKKEI_225**
Mean	0.014093	0.004218	0.011338
Median	0.030734	0.002364	0.000000
Maximum	10.95720	9.384339	13.23458
Minimum	-9.469514	-9.265572	-12.11103
Std. Dev.	1.228697	1.207556	1.497589
Skewness	-0.216810	-0.139326	-0.440371
Kurtosis	12.62812	10.05883	10.39159
Jarque-Bera	14297.12	7681.169	8528.729
ARCH 1-2	213.5 [0.00]	130.78 [0.000]	374.4 [0.000]
ARCH 1-5	132.2 [0.00]	122.28 [0.000]	173.9 [0.000]
ARCH 1-10	81.7 [0.00]	69.83 [0.000]	94.8 [0.000]
Q(20)	82.1 [0.00]	56.72 [0.000]	12.7 [0.000]
$Q^2(20)$	3170.5 [0.00]	2457.5 [0.000]	2463.3 [0.000]
Observations	3694	3694	3694

Table 2.2 : Descriptive statistics of Asian stock market return series.

	BIST_100	**IDX**	**SENSEX**	**MALAYSIA KLCI**
Mean	0.046152	0.067649	0.053008	0.023441
Median	0.037818	0.060711	0.027992	0.010344
Maximum	12.12721	7.623121	15.98998	4.2587
Minimum	-13.34085	-10.95400	-11.80918	-9.9785
Std. Dev.	1.856294	1.361725	1.446564	0.73692
Skewness	-0.125729	-0.715053	-0.083495	-0.866894
Kurtosis	7.530263	10.57476	12.30968	15.50074
Jarque-Bera	3168.607	9146.065	13344.28	24514.98
ARCH 1-2	29.89 [0.000]	100.81 [0.000]	30.03 [0.00]	71.9 [0.00]
ARCH 1-5	33.30 [0.000]	50.76 [0.000]	33.24 [0.00]	42.5 [0.00]
ARCH 1-10	20.67 [0.000]	28.48 [0.000]	28.95 [0.00]	29.33 [0.00]
Q(20)	42.34 [0.000]	91.82 [0.000]	54.05 [0.00]	45.5 [0.00]
$Q^2(20)$	596.15 [0.000]	147.81 [0.000]	835.7 [0.00]	752.9 [0.00]
Observations	3694	3694	3694	3694

Table 2.3 : Descriptive statistics for Latin American stock market returns (2002-2016).

	IPC	IPSA	MERVAL	BOVESPA
Mean	0.052131	0.030981	0.102688	0.031078
Median	0.041880	0.006231	0.023746	0.000000
Maximum	10.44071	11.80337	12.59611	13.67942
Minimum	-7.266123	-7.188170	-12.95163	-12.09605
Std. Dev.	1.231553	0.986046	2.054744	1.743733
Skewness	0.073498	-0.001941	-0.341309	-0.062366
Kurtosis	9.132839	13.06443	7.284588	7.722218
Jarque-Bera	5792.395	15590.65	2897.275	3434.635
ARCH 1-2	94.47 [0.000]	87.55 [0.000]	81.22 [0.000]	229.18 [0.000]
ARCH 1-5	80.31 [0.000]	74.25 [0.000]	58.2 [0.000]	125.78 [0.000]
ARCH 1-10	58.09 [0.000]	51.73 [0.000]	29.8 [0.000]	90.969 [0.000]
Q(20)	49.88 [0.000]	113.8 [0.000]	43.5 [0.000]	49.43 [0.000]
$Q^2(20)$	2353.7 [0.000]	962.3 [0.000]	824.8 [0.000]	3102.7 [0.000]
Observations	3694	3694	3694	3694

Table 2.4 : Descriptive statistics for Latin American stock market returns (2008-2015).

	BOVESPA	COLCAP	IPC	IPSA	MERVAL
Mean	-0.004925	0.021814	0.031353	0.026211	0.108438
Median	-0.014592	0.060330	0.035648	0.041989	0.149561
Maximum	15.47418	8.731454	11.11152	15.02507	14.28974
Minimum	-1.209.607	-8.923.942	-7.266.123	-7.173.023	-1.319.035
Std. Dev.	1.976140	1.184264	1.406739	1.197716	2.340949
Skewness	0.128723	-0.404428	0.322927	0.762753	-0.54893
Kurtosis	9.532895	9.410213	10.48861	22.51622	7.612456
Jarque-Bera	2814.046	2748.217	3719.344	25227.99	1479.936
ARCH 1-2	124.45 [0.000]	275.54 [0.000]	68.138 [0.000]	18.836 [0.000]	60.808 [0.000]
ARCH 1-5	79.300 [0.000]	118.96 [0.000]	66.070 [0.000]	22.061 [0.000]	42.714 [0.000]
ARCH 1-10	74.937 [0.000]	64.642 [0.000]	61.750 [0.000]	15.527 [0.000]	27.105 [0.000]
Q(20)	28.270 [0.103]	55.992 [0.000]	60.893 [0.000]	59.664 [0.000]	34.174 [0.025]
$Q^2(20)$	2378.7 [0.000]	1431.7 [0.000]	2042.6 [0.000]	346.52 [0.000]	825.44 [0.000]
Observations	1580	1580	1580	1580	1580

Figure 2.1-2.5 illustrates time series plots of stock prices and returns. Figure 2.1 displays the daily stock market indices over the sample period. As illustrated in this figure, it can be observed a similar trend for all stock markets, a sharp decrease from 2007 to 2008, which corresponds to the global financial crisis.

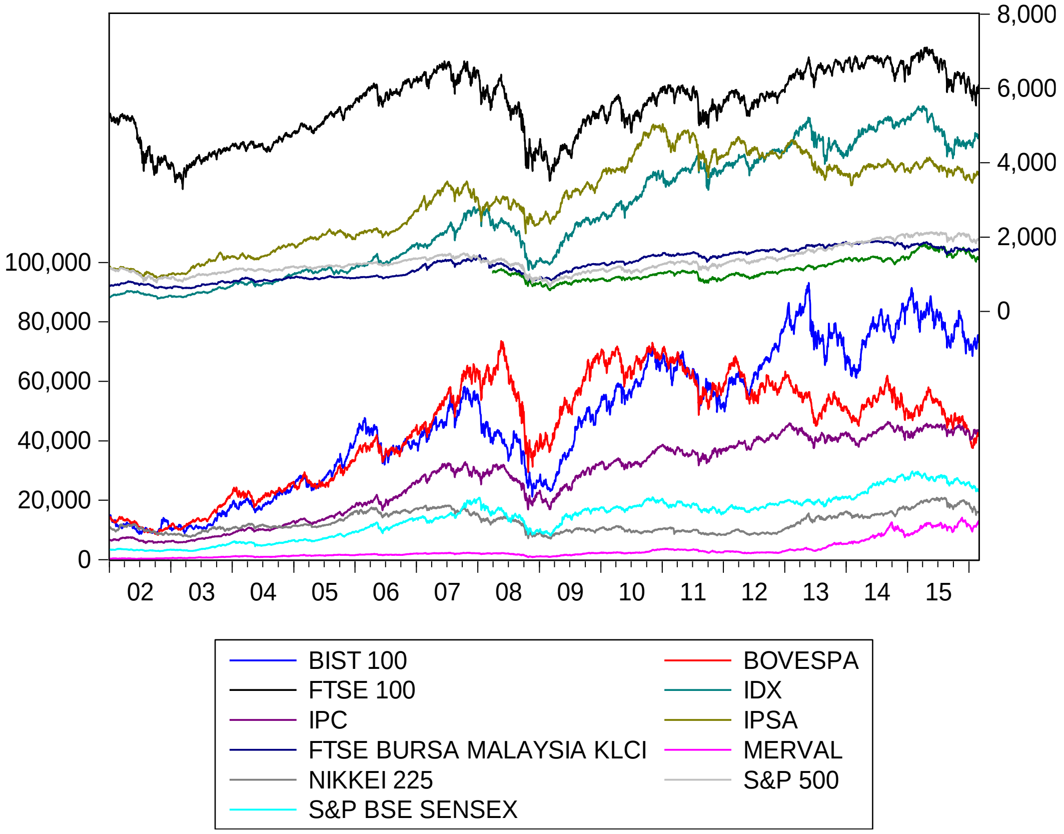

Figure 2.1 : Time series plots of stock market indices.

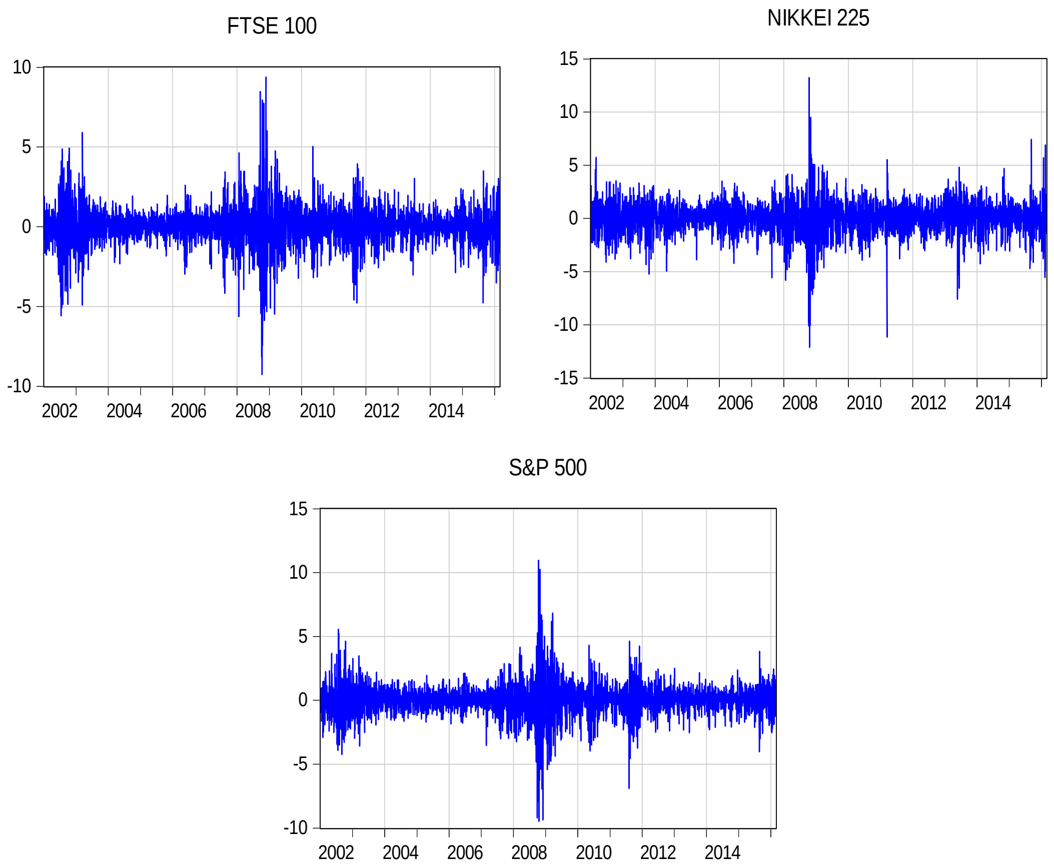

Figure 2.2 : Time series plots of developed stock market returns.

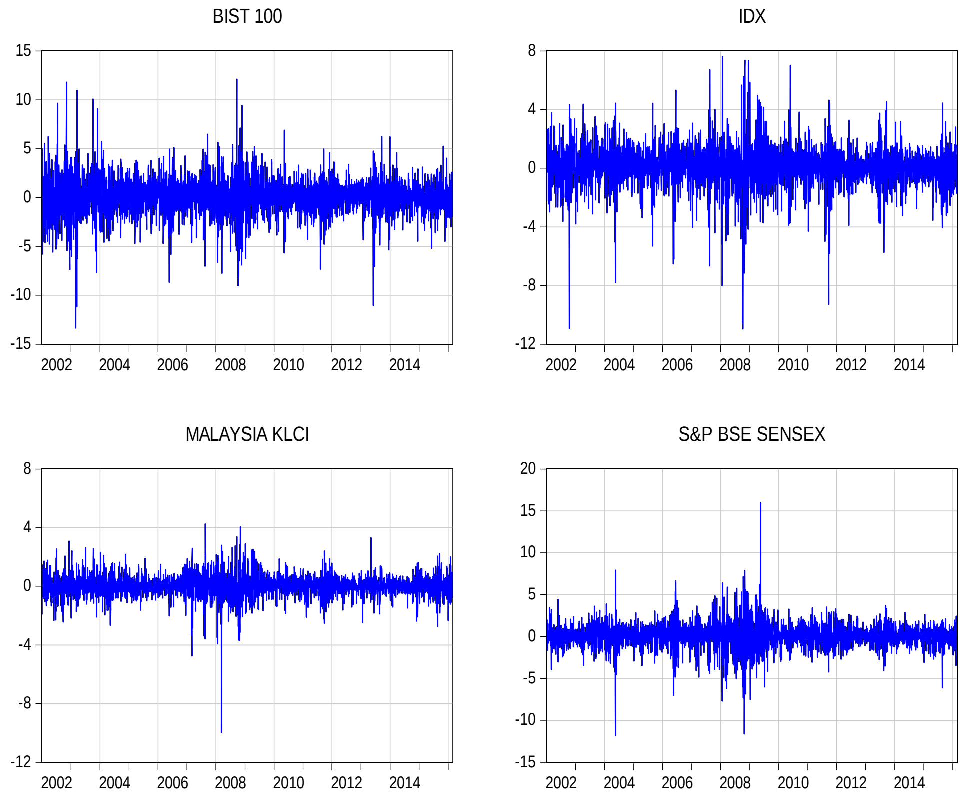

Figure 2.3 : Time series plots of developing Asian stock market returns.

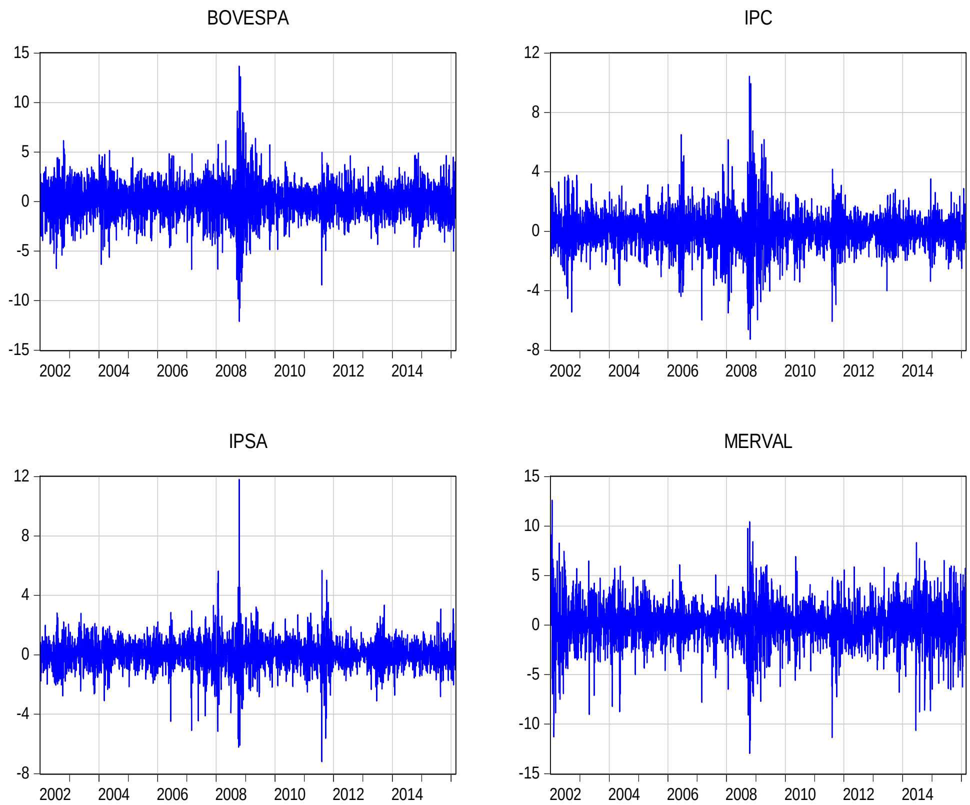

Figure 2.4 : Time series plots of developing Latin American stock market returns (except COLCAP, 2002-2016)

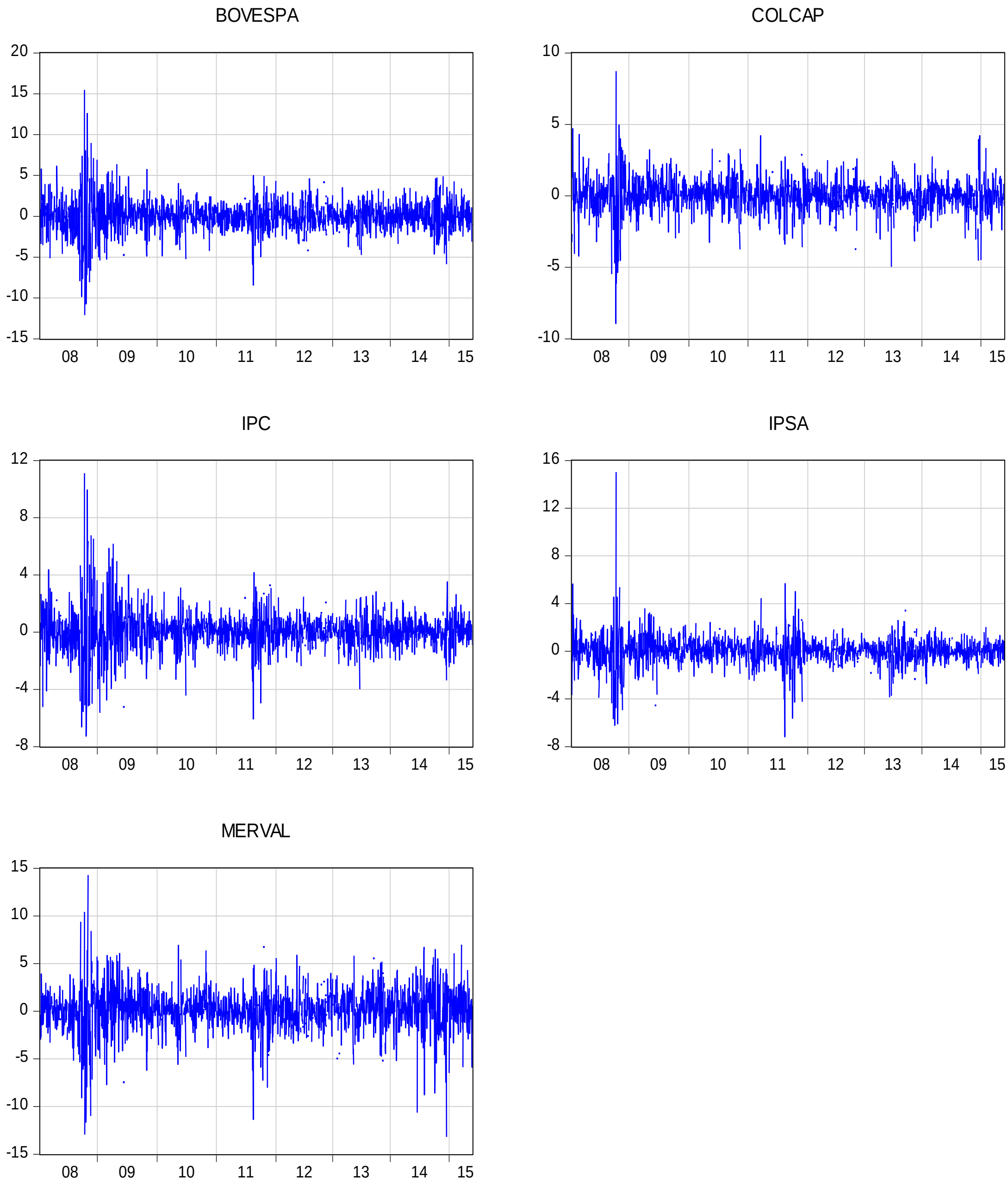

Figure 2.5 : Time series plots of Latin American stock market returns (including COLCAP, 2008-2015).

2.4 Methodology

The presence of long memory in dataset implies the persistence of observed autocorrelations. Recent researches agree with the importance of long memory and structural breaks in modelling volatility (Arouri et al, 2012). When structural changes occur in a stationary short memory process, the estimate of the fractional differencing parameter ‘d’ is biased away from zero, and shocks to volatility process exhibit a slow rate of decay (Diebold and Inoue, 2001; Perron and Qu, 2007). In their study, Choi &

Zivot (2007) suggested that structural breaks can seriously influence the results of long memory tests and generate spurious long memory process.

2.4.1 Long memory tests

In this section, various tests of long memory were used to analyze for long memory characteristic of stock market volatility.

Long memory is characterized by a slowly decaying autocovariance function. When long memory process exists in volatility then various forms of GARCH models can be used which take into account long memory property.

In this study, using the Hurst-Mandelbrot Rescaled Range (R/S) statistics, Lo (1991), Rescaled Range R/S, Geweke and Porter-Hudak (1983) (GPH), and the Robinson and Hendry (1999) Gaussian Semiparametric (GSP) test statistics, long memory components in the returns were tested. In addition, considering long memory in the volatility process, these tests were applied to stock market indices' squared returns, which are widely regarded as a proxy of conditional volatility (Choi & Hammoudeh, 2009; Lobato & Savin, 1998). These tests have been extensively used in the related literature.

2.4.1.1 Rescaled Range (R/S) statistics

Rescaled range statistic R/S is one of the oldest and famous test introduced by Hurst (1951), which investigates the presence of long-term memory in time series. In their studies, Mandelbrot and Wallis (1969) discovered a number of series with infinite memory. Nevertheless, that kind of time series may have quite likely finite memory cycles that are longer than their sample period, and therefore they have drawn a conclusion of infinite memory. Mandelbrot (1971) suggested that R/S analysis can be used in economic and financial investigations. Standard autocorrelation tests detect long-term dependency in stock market prices if dependent behavior is periodic and if the periodicity is consistent over time. The Hurst exponent is used as a measure of long-term dependence for a given nonperiodic cycles, and point out the average duration of the dependency may last. Basically, Rescaled range statistic R/S is the range of partial sums of deviations of a time series from its mean scaling with its standard deviation. Hence, Hurst exponent H stands for the scaling behavior of the range of cumulative departures of a time series from its mean. Formally, the range R of a time series $\{x_t\}$, $t = 1,...,T$ is determined as:

$$R_T = \max_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) - \min_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) \tag{2.7}$$

Here, *x* is given as an estimate of the sample mean. The classical rescaled range is the best known *R/S* statistic:

$$R/S = \hat{\sigma}^{-1} \left[\max_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) - \min_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) \right], \ \hat{\sigma}^2 = T^{-1} \sum_{t=1}^{T} (x_t - \bar{x})^2 \tag{2.8}$$

This statistic is robust to non-normality, but in the presence of autocorrelation the coefficients may be biased. Consequently, Lo (1991) developed a modified rescaled range Q_T, which adjusts for possible short term dependence by applying the Newey West heteroscedasticity and autocorrelation consistent estimator instead of the sample standard deviation *S*:

$$Q_T = S_T^{-1} \left[\max_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) - \min_{1 \le t \le T} \sum_{t=1}^{T} (x_t - \bar{x}) \right] \tag{2.9}$$

$$S_T^2 = S^2 + \frac{2}{T} \sum_{j=1}^{\tau} \omega_j(\tau) \left\{ \sum_{i=j+1}^{T} (x_i - \bar{x})(x_{i-j} - \bar{x}) \right\},$$

$$\omega_j(\tau) = 1 - \frac{j}{\tau + 1}$$

While Mandelbrot's null hypothesis is "there is no autocorrelation", Lo's null hypothesis is "there is no long-term dependence".

2.4.1.2 Geweke and Porter-Hudak (GPH) model

Geweke and Porter-Hudak (1983) suggested a semi-nonparametric approach to testing for long memory in the sense of fractionally integrated process. Furthermore, Geweke and Porter-Hudak (1983) used Fourier transformation and spectral density into the following formula:

Let r_t be the return series. The GPH estimator of the long memory parameter d for r_t can be then determined using the following periodogram:

$$\log\left[I(w_j)\right] = \beta_0 + \beta_1 \log\left[4\sin^2\left(\frac{w_j}{2}\right)\right] + \varepsilon_j \tag{2.10}$$

where $w_j = 2\pi j / T$, $j = 1, 2, ..., n$; ε_j is the residual term and w_j represents the $n = \sqrt{T}$ Fourier frequencies. $I(w_j)$ stands for the sample periodogram defined as

$$I(w_j) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} r_t e^{-w_j t}\right|^2$$

where r_t is presumed to be a covariance stationary time series. The estimate of fractional difference parameter d, namely $\hat{d}_{GPH}$, is $-\hat{\beta}_1$. GPH test for the null hypothesis “there is no long memory (d=0)”.

2.4.1.3 Gaussian semiparametric (GSP) method

Gaussian Semiparametric estimation method which has been introduced by Robinson and Henry (1999) is based on the specification of the shape of the spectral density of the time series.

The Robinson and Henry (1999)’s GSP estimator of the long memory parameter for a covariance stationary series, which is consistent and asymptotically normal under certain regularity conditions, is given by

$$f(w) = Gw^{1-2H} \text{ as } w \to 0^+ \tag{2.11}$$

where $\frac{1}{2} < H < 1$, $0 < G < \infty$ and $f(w)$ is the spectral density of r_t. The periodogram with respect to the observations of r_t, $t = 1, ..., T$ is defined as

$$I(w_j) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} r_t e^{itw_j}\right|^2 \tag{2.12}$$

Accordingly, the Hurst exponent parameter H is obtained by minimizing the following function $R(H)$.

$$H = \underset{\Delta_1 \le H \le \Delta_2}{\arg\min}\, R(H)$$

where

$$
\begin{cases}
0 < \Delta_1 < \Delta_2 < 1 \\
R(H) = \log\left\{ \dfrac{1}{m} \sum_{j=1}^{m} \dfrac{I(w_j)}{w_j^{1-2H}} \right\} - (2H-1)\dfrac{1}{m}\sum_{j=1}^{m} \log(w_j) \\
m \in \left(0, [n/2]\right) \\
w_j = 2\pi j / T
\end{cases}
$$

2.4.2 Structural breaks test in variance

As shown by Hillebrand (2005), the presence of structural breaks in the unconditional variance of the series could lead to the overestimation of the size of the GARCH parameters and cause the sum of estimated GARCH parameters to converge to one. In fact, Van Dijk, et al. (2005) and Rodrigues and Rubia (2007) proved that severe size distortions in causality in variance tests occur when there are structural breaks in the variance of series. Moreover, as argued by Acatrinei et al. (2013), if data have structural breaks, the conditional correlation models may lead to incorrect estimation of the risk. Since conditional variances are obtained from a univariate GARCH model in the first step of the DCC model, ignoring the structural breaks could lead to misleading results and thereby could distort the second step estimation. Thus the univariate GARCH models used in the first step to estimate the DCC GARCH models take into account the structural breaks in variance. Hence, before estimating DCC-GARCH model, structural breaks tests in variance were proceeded. Among the several tests for breaks in variance, Sansó et al.'s (2004) second statistic known as the Kappa-2 (κ2) statistic was carried out, which is more appropriate in case where both the normality assumption does not hold and there are ARCH effects as well. The (κ2) statistic can be defined as follows:

$$\kappa_2 = \sup_k \left| T^{-0.5}\, G_k \right| \tag{2.13}$$

where $G_k = \hat{\omega}^{-0.5} \left| C_k - \frac{k}{T}\, C_T \right|$, $C_k = \sum_{t=1}^{k} r_t^2$ k=1,2…T , $r_t \sim iid(0,\sigma^2)$ and $\hat{\omega}$ is a consistent estimator of ω. A non-parametric estimator of ω is given by:

$$\hat{\omega} = \frac{1}{T}\sum_{t=1}^{T}\left(r_t^2 - \hat{\sigma}^2\right)^2 + \frac{2}{T}\sum_{l=1}^{m}\omega(l,m)\sum_{t=l+1}^{T}\left(r_t^2 - \hat{\sigma}^2\right)\left(r_{t-1}^2 - \hat{\sigma}^2\right) \tag{2.14}$$

where $\omega(l,\ m)$ is a lag window, such as the Bartlett, defined as $\omega(l,\ m) = l - l/(m+1)$, or the quadratic spectral.

2.4.3 Modelling long memory in volatility

2.4.3.1 The fractional integrated GARCH (FIGARCH) model

As mentioned before commonly high frequency financial data follows a pattern that yield a sum of α_1 and β_1 (ARCH and GARCH parameters) close to 1, with α_1 small and β_1 large. Therefore, the effect of shocks on conditional variance diminishes very slowly. Baillie et al. (1996) suggested the class of Fractionally Integrated GARCH (FIGARCH) models. Fractionally integrated processes are different from both stationary and unit-root processes with their persistence and mean reverting features. Formally, the FIGARCH (1,d,1) can be defined with lag operator "L" as follows

$$h_t = \omega + \beta h_{t-1} + \left[1 - \left(1 - \beta L^{-1}\right)\left(1 - \lambda L\right)\left(1 - L\right)^d\right]\varepsilon_t^2 \tag{2.15}$$

where $\omega > 0$, $\beta \prec 1$ and $\lambda < 1$. The fractional integration parameter d reflects the degree of long memory or the persistence of shocks to conditional variance, and satisfies the condition $0 \le d \le 1$. If $0 < d < 1$, the model implies an intermediate range of persistence and especially the volatility shocks disperse only at a hyperbolic rate. The integration parameter $d = 0$ indicates that the model has a short memory and reduces to the GARCH (1,1) model. On the other hand, if $d = 1$, model transforms to IGARCH (1,1) whose variance process is no longer mean-reverting (Chkili et al. 2014).

2.4.3.2 FIAPARCH model

Tse (1998) proposed fractionally integrated asymmetric power (FIAPARCH) model which allows persistence (long memory) and asymmetry effects in the conditional volatility. FIAPARCH model takes the following form:

$$h_t^{\delta/2} = \omega\left(1 - \beta L\right)^{-1} + \left[1 - \left(1 - \beta L\right)^{-1}\left(1 - \lambda L\right)\left(1 - L\right)^d\right]\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^\delta \tag{2.16}$$

where $\omega \succ 0, \delta > 0, \beta \prec 1, and\, \lambda < 1$.

The asymmetry parameter γ satisfies the condition $-1 < \gamma < 1$. When $\gamma > 0$ indicates that negative shocks are more effective on volatility than positive shocks of equal dimension. From Equation (2.16) we can see the fractional integration parameter d lies between zero and 1, $0 \le d \le 1$, like in FIGARCH model, and holds long memory property in the conditional variance process. When γ = 0 and δ = 2, the FIAPARCH model degrades to the FIGARCH model and when d = 0, it reduces to the APARCH model. Conrad et al. (2011) argue that a sufficient condition for the conditional variance h_t to be positive almost surely for all t is that $\gamma > -1$ and the parameter combination (λ, d, β) satisfies the inequality constraints stated in Conrad and Haag (2006) and Conrad (2010).

2.4.4 DCC GARCH model with structural breaks

In the first step of the Engle (2002) DCC-estimation process, the GARCH parameters are estimated. In the second step, the standardized residuals are used to estimate the time-varying correlation matrix.

$$H_t = D_t R_t D_t \tag{2.17}$$

H_t is a $n \times n$ conditional covariance matrix, R_t is the conditional correlation matrix, and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag(h_{1,t}^{1/2}, \ldots h_{n,t}^{1/2}) \tag{2.18}$$

$$R_t = diag(q_{1,t}^{-1/2}, \ldots q_{n,t}^{-1/2})\ \mathrm{Q}_t diag(q_{1,t}^{-1/2}, \ldots q_{n,t}^{-1/2}) \tag{2.19}$$

The elements of H_t for the GARCH (1,1) model:

$$\mathrm{h}_{i,t} = w_i + \alpha_i \varepsilon^2{}_{i,t-1} + \beta_i \mathrm{h}_{i,t-1} + \gamma_i\ \mathrm{DU}_{i,t} \tag{2.20}$$

Where $DU_{i,t}$ is a vector of dummy variables for country i at time t which takes value of one at the time of structural breaks in variance and zero otherwise.

Q_t is a symmetric positive definite matrix.

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1(z_{t-1}z_{t-1}') + \theta_2 Q_{t-1} \tag{2.21}$$

$\bar{\mathrm{Q}}$ is the $n \times n$ unconditional correlation matrix of the standardized residuals z_{it} $(z_{it} = \varepsilon_{i,t} / \sqrt{h_{i,t}})$. The parameters θ_1 and θ_2 are positive and $\theta_1 + \theta_2$ is smaller than one, therefore the DCC model is mean reverting. The time-varying correlation coefficient $\rho_{i,j,t}$ for $\mathrm{i} \neq \mathrm{j}$ is,

$$\rho_{ij,t} = \frac{(1-\theta_1-\theta_2)\bar{Q} + \theta_1(z_{t-1}z_{t-1}') + \theta_2 Q_{t-1}}{\sqrt{\left[(1-\theta_1-\theta_2)\bar{Q} + \theta_1 z^2{}_{i,t-1} + \theta_2 Q_{t-1}\right]}\sqrt{\left[(1-\theta_1-\theta_2)\bar{Q} + \theta_1 z^2{}_{j,t-1} + \theta_2 Q_{t-1}\right]}} \tag{2.22}$$

2.5 Preliminary Results of Empirical Modeling

2.5.1 Long memory tests

As can be seen from the Tables 2.5-2.15, the long memory property in squared return of all market indices is analyzed by using test statistics of Hurst-Mandelbrot R/S, Lo R/S, GPH and GSP. Hence these test statistics reject the null hypothesis of no long range dependence, the squared return series exhibit the long memory effect. The long memory tests indicate favorably on the presence of the long memory effect at the 1% level. Since d parameter falls in the interval (0, 0.5) demonstrates that the squared return series follow the long memory process.

To sum up, the long memory tests suggest that for modeling and forecasting of stock return volatility it would be more appropriate to use GARCH models allowing for long memory property. In what follows we model volatility using GARCH models taking into account long memory behavior of squared returns.

Table 2.5 : Long Memory Test for S&P 500 return and S&P 500 squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.259058 (0.020747)	0.279745 (0.0155568)
Test Statistics	5.34993	4.86668		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.6 : Long Memory Test for FTSE 100 return and FTSE 100 squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.341208 (0.020747)	0.284979 (0.0155568)
Test Statistics	4.82101	4.33839		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.7 : Long Memory Test for NIKKEI 225 squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.444562 (0.020747)	0.386129 (0.0155568)
Test Statistics	4.0966	3.76238		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.8 : Long Memory Test for BOVESPA squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.177814 (0.0163172)	0.17798 (0.0116342)
Test Statistics	4.80301	4.45945		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.9 : Long Memory Test for IPC squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.139132 (0.0163172)	0.170868 (0.0116342)
Test Statistics	5.7302	5.32149		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.10 : Long Memory Test for IPSA squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.179554 (0.0163172)	0.176587 (0.0116342)
Test Statistics	4.21471	3.76373		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.11 : Long Memory Test for MERVAL squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.211888 (0.0163172)	0.198649 (0.0116342)
Test Statistics	3.91649	3.49185		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.12 : Long Memory Test for BIST 100 squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.163422 (0.0163172)	0.149 (0.0116342)
Test Statistics	4.28864	3.99969		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.13 : Long Memory Test for IDX squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.202075 (0.0163172)	0.17827 (0.0116342)
Test Statistics	3.95906	3.65753		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.14 : Long Memory Test for S&P BSE SENSEX squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.153453 (0.0163172)	0.159749 (0.0116342)
Test Statistics	5.68119	5.20614		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 2.15 : Long Memory Test for MALAYSIA KLCI squared return.

SQUARED RETURN	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.113185 (0.0163172)	0.120551 (0.0116342)
Test Statistics	4.20606	3.99785		
Critical values			Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

2.5.2 Estimates of GARCH-type models

This part of the thesis analyzes the volatility properties of stock market returns. Multivariate DCC-GARCH model, AR(1)-DCC-FIGARCH and AR(1)-DCC-FIAPARCH model were estimated among emerging and developed stock markets over the period 2002-2016. Unlike the earlier studies, the breaks in variance were taken into account to analyze the volatility spillovers among the Latin American stock markets in the period 2008-2015.

The dates for structural breaks in variance from the kappa-2 (κ2) statistics are illustrated in Table 2.16. As mentioned above, after carrying out the structural breaks tests I turn to DCC-GARCH estimation.

Table 2.16 : Break in variance test.

Sansó et al. (2004) Kappa-2	No. of breaks	Break dates
BRAZIL	1	24.06.2009
COLOMBIA	3	04.03.2008
		12.09.2008
		09.12.2008
MEXICO	5	31.03.2008
		11.09.2008
		05.12.2008
		14.07.2009
		28.06.2010
CHILE	1	19.06.2009
ARGENTINA	6	11.09.2008
		28.11.2008
		14.07.2009
		02.08.2011
		03.01.2012
		05.06.2014

On the other hand, it was obtained dynamic conditional correlations from fractionally integrated process that consider long memory property in volatility. Table 2.17 reports the estimation results under the Student-t distributed innovations of the AR(1)-DCC-FIGARCH (1,d,1) model of the developed markets. As seen, the AR (1) parameter is negative and statistically significant for S&P 500 and FTSE 100 indices, implying that past stock returns are negatively correlated with current returns. However, the AR (1) parameter of the NIKKEI 225 index is statistically insignificant that indicates past information about stock returns are uncorrelated with current stock returns.

Furthermore, the fractional integration coefficients d’s are significant at 1% level of significance for all returns indicating that all volatility processes are persistent over time.

Table 2.17 : Empirical results for developed market index returns.

	S&P 500	FTSE100	NIKKEI225
Estimation Method	FIGARCH	FIGARCH	FIGARCH
AR(1)	-0.064***	-0.049***	-0.015
Cst(M)	0.049***	0.040***	0.059***
Cst(V)	0.032***	0.024***	0.053***
d-Figarch	0.682***	0.560***	0.589***
ARCH(Alpha1)	0.016	0.091*	0.147***
GARCH(Beta1)	0.671***	0.569***	0.652***
No. Observations	3694	3694	3694
No. Parameters	6	6	6
Log Likelihood	-5051.65	-5080.544	-6224.842
AIC	8.296	8.296	8.296

*, **, and *** indicate the significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Tables 2.18-2.19 illustrate the estimation results of the AR(1)-DCC-FIAPARCH (1,d,1) based on Student-t distributions for the developing stock markets. In Table 2.18 and 2.19, the AR (1) parameters are positive and statistically insignificant for BIST 100 and BOVESPA indices, implying that past stock returns are uncorrelated with current returns. However, the AR (1) parameters of the other Asian and Latin American market indices are positive and statistically significant at the one percent level that indicates past information about stock returns is instantaneously and rapidly embodied in the current stock returns.

The leverage effect is measured by the coefficient Gamma (γ), while Delta (δ) is the power term parameter that takes finite positive values. The significance of the power term (δ) leads to rejection of the null hypothesis of $\delta = 2$ in all cases, supporting that use of the FIAPARCH specification is appropriate. Leverage effect coefficients (γ) are positive and statistically significant in all cases suggesting negative shocks are more effective on volatility than positive shocks of same magnitude. Moreover, the fractional integration coefficients d are significant at the one percent level indicating that all volatility processes are persistent over time.

Table 2.18 : Empirical results for Asian market index returns.

	BIST 100	IDX	SENSEX	MALAYSIA
Estimation Method	FIAPARCH	FIAPARCH	FIAPARCH	FIAPARCH
AR(1)	0.025	0.096***	0.081***	0.142***
Cst(M)	0.07***	0.063***	0.051***	0.023***
Cst(V)	6.703***	2.751***	2.38***	1.115***
d-Figarch	0.393***	0.310***	0.383***	0.354***
ARCH(Alpha1)	0.196***	0.304***	0.142***	0.087
GARCH(Beta1)	0.498***	0.463***	0.447***	0.329**
APARCH(Gamma1)	0.342***	0.612***	0.454***	0.305***
APARCH(Delta)	1.545***	1.383***	1.598***	1.643***
No. Observations	3694	3694	3694	3694
No. Parameters	8	8	8	8
Log Likelihood	-7165.41	-5849.24	-5932.72	-3566.82
AIC	11.496	11.496	11.496	11.496

*, **, and *** indicate the significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Table 2.19 : Empirical results for Latin American market index returns.

	BOVESPA	IPC	IPSA	MERVAL
Estimation Method	FIAPARCH	FIAPARCH	FIAPARCH	FIAPARCH
AR(1)	0.000	0.065***	0.180***	0.061***
Cst(M)	0.014	0.034**	0.028*	0.099***
Cst(V)	0.241***	0.064***	0.062***	0.450
d-Figarch	0.260***	0.338***	0.461***	0.202***
ARCH(Alpha1)	0.115	0.254***	0.202***	-0.390***
GARCH(Beta1)	0.344***	0.520***	0.538***	-0.260
APARCH(Gamma1)	0.561***	0.748***	0.390***	0.131**
APARCH(Delta)	1.608***	1.468***	1.477***	2.284***
No. Observations	3694	3694	3694	3694
No. Parameters	8	8	8	8
Log Likelihood	-6884.825	-5384.575	-4551.473	-7488.740
AIC	11.883	11.883	11.883	11.883

*, **, and *** indicate the significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

2.5.3 Multivariate GARCH specifications and financial contagion

In this part, by analyzing dynamic conditional correlations the presence of contagion were tested. A two stage procedure was used. In the first stage, time varying conditional correlations were estimated and the characteristics of these correlations were analyzed. Second, dynamic conditional correlations were regressed on dummy variables which stand for various financial events.

The results for stock markets in developed countries are presented in Table 2.20. The coefficients are significant. The dynamic conditional correlations obtained from DCC FIGARCH model are shown in Figure 2.6. The dynamic conditional correlations between S&P 500 and FTSE 100 indices are the highest. Dynamic conditional correlations among S&P 500 reveal strong correlations with FTSE 100. For these markets the correlations are above 0.5 suggesting higher integration between them. On the other hand, on average the correlations between NIKKEI 225 and other markets are less than 0.24. This result indicate that there is portfolio diversification opportunities between NIKKEI 225 and other developed markets. However, as one can see from Figure 2.6 and 2.7, correlations between NIKKEI 225 and FTSE 100 begin to increase in 2007 prior to the United States (U.S.) subprime mortgage crisis and at the end of 2008 it reaches its highest level when several major financial institutions collapsed in September 2008. In addition in August 2015 correlation between NIKKEI 225 and FTSE 100, and NIKKEI 225 and S&P 500 suddenly increase. This increase arose from the 2015–16 stock market selloff which began in the United States on August 18, 2015.

Table 2.20 : AR(1)-DCC-FIGARCH coefficients.

Coefficient	Value	Prob.
ρ FTSE 100 - S&P 500	0.567977	0.00
ρ NIKKEI 225 - S&P 500	0.141035	0.00
ρ NIKKEI 225 - FTSE 100	0.233082	0.00
α	0.0039	0.00
β	0.9948	0.00
ν	8.72	0.00
LogLikelihood	-15298.74	
Li-McLeod(50)	1695.03	0.00
Li-McLeod Squared(50)	839.47	0.00

ρ is correlation coefficient, α is ARCH term , β is GARCH term, ν is degrees of freedom for t distribution. Li-McLeod is Multivariate Portmanteau Statistics on Standardized Residuals, Li-McLeod Squared is Multivariate Portmanteau Statistics on Squared Standardized Residuals.

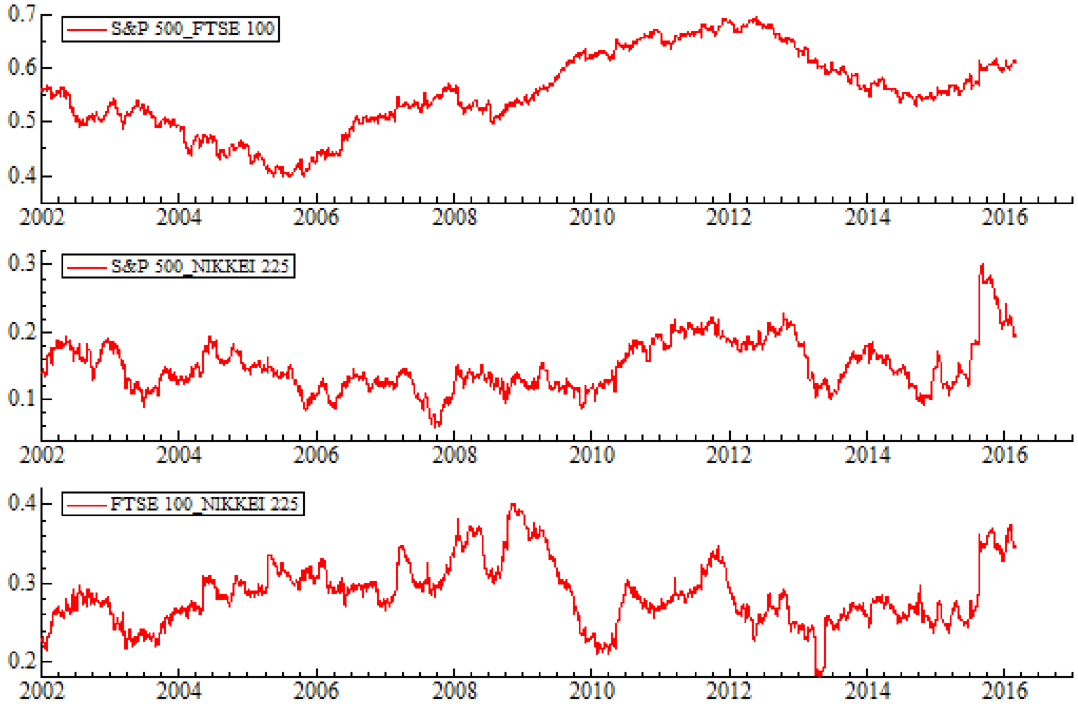

Figure 2.6 : Dynamic conditional correlations between NIKKEI 225 and the others (separately).

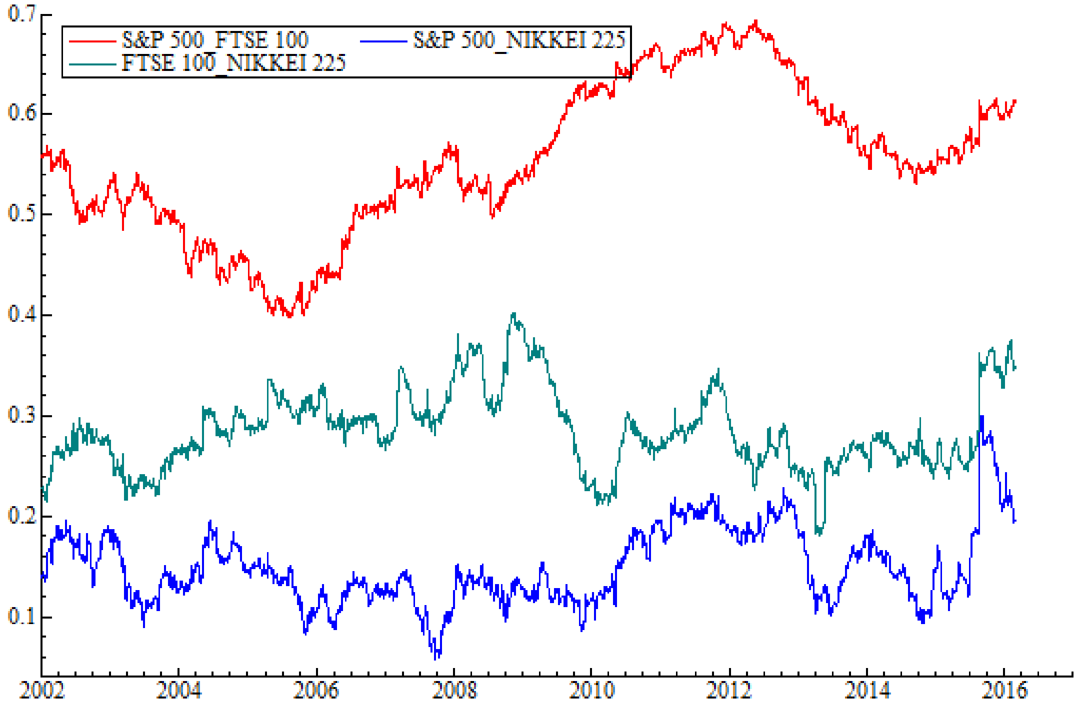

Figure 2.7 : Dynamic conditional correlations of developed countries stock returns.

According to the definition of contagion as an increase of the correlation coefficient in a crisis period compared to a benchmark period, it can be seen that these findings signal financial contagion effects between United Kingdom, United States and Japan. In order to test this change in dynamic correlation, dummy variable was constituted equal to unity for the corresponding phase of event and zero otherwise;

$$\rho_{ij,t} = c_0 + \psi\rho_{ij,t-1} + \sum_{k=1}^{k} \zeta dummy_{k,t} + \upsilon_{ij,t.} \tag{2.23}$$

c_0 is a constant term, and the first lag of the dynamic correlation $\rho_{ij,t-1}$ is inserted into the model to remove the serial correlation. In Equation 2.23 i and j correspond to countries stock markets, and k=1,…,k are the numbers of dummy variables corresponding to the phase of events.

Moreover, all the DCCs present strong evidence of heteroskedasticity with significant null hypothesis of the ARCH tests. Following Chiang et al. (2007), and Kang et al. (2016) we use a GARCH (1,1) model including dummy variables as follows:

$$h_{ij,t} = \delta_0 + \delta_1 h_{ij,t-1} + \delta_2 \upsilon^2_{ij,t-1} + \sum_{k=1}^{k} \lambda_k dummy_{k,t} \tag{2.24}$$

According to this model, the significance of the estimated coefficients on the dummy variables indicates structural changes in mean and variance shifts of the correlation coefficients due to external shocks during the crisis periods.

The estimates are reported in Table 2.22. The evidence shows that none of the dummies in the mean equation is statistically significant, except selloff dummy. This indicate that the correlation during the crisis period is not significantly different from that of the normal period. On the other hand we may infer from the significant coefficient of stock market selloff that affect the dynamic conditional correlations.

This finding is consistent with the paths shown in Figure 2.6 and supports the hypothesis that the impact of the selloff phases increase, concretely speaking, the contagion effect between the Japan stock market (NIKKEI225) and US stock market (S&P500) and London Stock Exchange (FTSE100) market.

With regard to the variance equations in Panel B, the majority of all coefficients are statistically significant. The coefficient of global financial crisis dummy between NIKKEI 225 and S&P 500 is negative, indicating that volatility of conditional correlation dynamics decrease.

Especially, coefficient of Eurozone dummy in the equation for dynamic correlations between US stock market (S&P 500) and London Stock Exchange (FTSE 100) market is higher than the others. The evidence shows that Eurozone crisis has positive impact on the DCCs, implying that the exogenous shifts led to a rise in the volatility of the correlation between US stock market (S&P 500) and London Stock Exchange (FTSE 100) market. This finding can be explained by the higher economic activity during the event. However, the coefficient of Eurozone dummy in the equation for dynamic correlations between NIKKEI 225 and the others is negative and significant, indicating that volatility of conditional correlation dynamics decrease.

During tapering, the coefficient λ_3 between U.S. stock market (S&P 500) and London Stock Exchange (FTSE 100) market is statistically significant and positive, indicating that the tapering led to a rise in the volatility of the dynamic correlations between these developed markets. On the other hand, the coefficient of tapering dummy between NIKKEI 225 and S&P 500 is slightly positive.

In addition, stock market selloff has positive effect on the dynamic conditional correlations among all three markets, indicating that the exogenous shifts led to a rise in the volatility of the correlation between the Japan stock market (NIKKEI 225), US stock market (S&P 500) and London Stock Exchange (FTSE 100) market.

Table 2.21 : Financial and economic events.

Events	Time period
The global financial crisis	1/8/2007-4/11/2009
Eurozone sovereign debt crisis	5/11/2009-22/4/2010
FED Tapering	18/12/2013-30/9/2014
Stock market selloff	18/8/2015-25/8/2015

Table 2.22 : Impact of financial crisis on dynamic correlations between developed stock markets.

	FTSE 100-S&P 500	NIKKEI 225-S&P 500	NIKKEI 225-FTSE 100
Panel A: Mean equation			
C_0	0.0004	0.001***	0.0018***
ψ	0.99***	0.99***	0.99***
ζ_1	0.0001	-0.0003	0.0001
ζ_2	3.83E-05	0.0001	-0.0004
ζ_3	-8.88E-05	-0.0004	-0.0001
ζ_4	0.006**	0.016***	0.012***
Panel B: Variance equation			
δ_0	0.516***	0.144***	0.273***
δ_1	0.508***	0.602***	0.59***
δ_2	0.565***	0.45***	0.477***
$\lambda_{1\ \mathrm{GLOBAL}}$	0.022***	-0.020***	0.053***
$\lambda_{2\ \mathrm{EUROZONE}}$	0.113***	-0.021***	-0.05***
$\lambda_{3\ \mathrm{TAPERING}}$	0.051***	0.008***	-0.0074***
$\lambda_{4\ \mathrm{SELLOFF}}$	0.047***	0.065***	0.03***

Note:*, ** and *** indicate that statistics are significance at the 10%, 5% and 1% level of significant respectively.

As can be seen from Table 2.23, the coefficients for Asian stock markets are significant. The dynamic correlations obtained from AR(1)-DCC-FIAPARCH model are shown in Figure 2.8. On average the correlations among Asian stock markets are less than 0.5, whereas the correlations between Malaysia and Indonesia are around 0.4. These results indicate that Asian markets are weakly correlated. But at the end of 2007 correlations increase after that they suddenly drop in 2008 especially correlations between Indonesia (IDX) and all others.

Table 2.23 : AR(1)-DCC-FIAPARCH coefficients.

Coefficient	Value	Prob.
ρ IDX – BIST 100	0.225619	0.000
ρ SENSEX – BIST 100	0.246746	0.000
ρ MALAYSIA – BIST 100	0.179730	0.000
ρ SENSEX – IDX	0.324162	0.000
ρ MALAYSIA – IDX	0.423209	0.000
ρ MALAYSIA – SENSEX	0.246018	0.000
α	0.009306	0.010
β	0.978573	0.000
ν	7.171	0.000
LogLikelihood	-21193	
Li-McLeod(50)	1006.4	0.000
Li-McLeod Squared(50)	787.2	0.600

ρ is correlation coefficient, α is ARCH term , β is GARCH term, ν is degrees of freedom for t distribution. Li-McLeod is Multivariate Portmanteau Statistics on Standardized Residuals, Li-McLeod Squared is Multivariate Portmanteau Statistics on Squared Standardized Residuals.

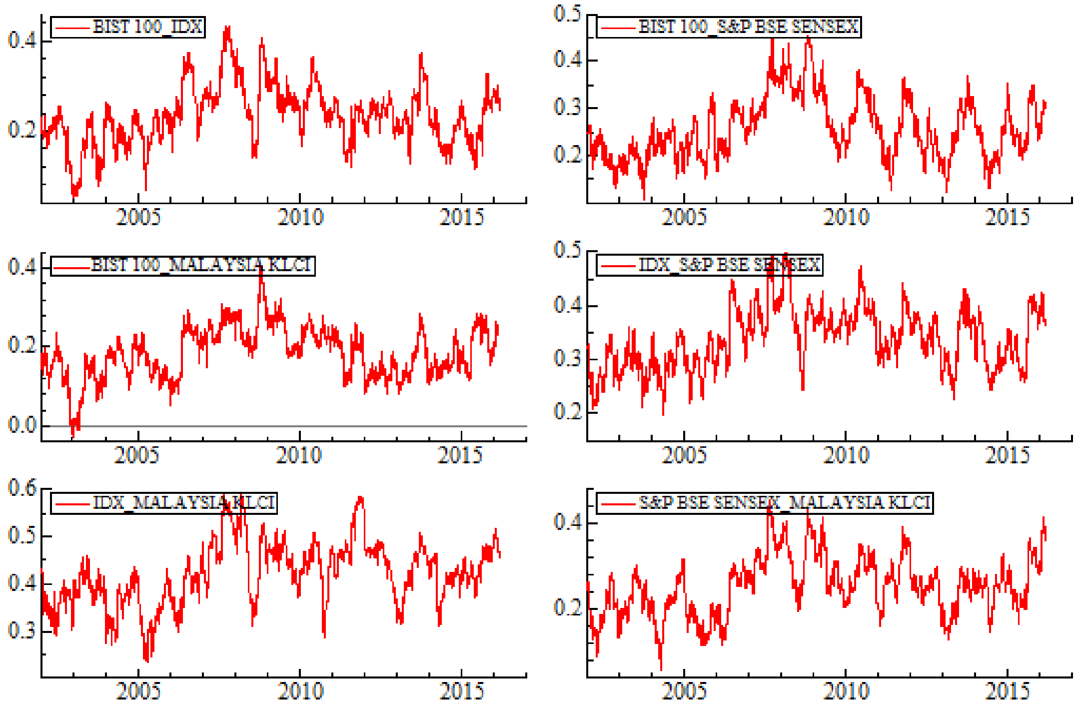

Figure 2.8 : Dynamic Conditional Correlations of Asian countries stock returns (separately).

Table 2.24 shows the estimation results of the inclusion of dummy variables on the conditional correlations between the Asian stock markets. In the mean equation of Panel A in the Table 2.24, the coefficient ζ_1 in the global financial crisis has either a statistically insignificant or slightly positive impact on correlations of BIST 100 and Malaysia, Indonesia, and India, indicating that the weak contagion effect between BIST 100 and these three markets. During the Eurozone crisis, the majority of coefficients ζ_2 are insignificant, implying that the Eurozone has no influence on the dynamic correlations. The coefficient ζ_3 represents the effect of the Tapering event is either negative or insignificant, indicating that conditional correlation dynamics either decrease or remain unchanged during the tapering. During stock market selloff, the majority of coefficients ζ_4 are slightly positive and statistically significant, implying that conditional correlation dynamics increase. Considering variance equations in Panel B, almost all of the coefficients λ have a significant and positive impact on the dynamic conditional correlations, supporting the contagion effect. On the other hand, during tapering the coefficient λ_3 is statistically significant and negative, indicating that the tapering led to a reduction in the volatility of the dynamic correlations between the Asian stock markets.

Table 2.24 : Impact of financial crisis on dynamic correlations between Asian markets.

	BIST 100-MALAYSIA	BIST 100-IDX	BIST 100-SENSEX	SENSEX-MALAYSIA	IDX-MALAYSIA	IDX-SENSEX
Panel A: Mean equation						
C_0	0.0024***	0.002***	0.003***	0.002***	0.003***	0.004***
ψ	0.985***	0.986***	0.986***	0.99***	0.991***	0.986***
ζ_1	0.001***	0.0008*	0.001**	0.000496	0.000444	0.000668
ζ_2	0.001**	0.000369	0.000492	0.000285	0.000527	0.000602
ζ_3	-5.00E-04	-0.001**	-0.0011**	-0.000249	-0.000299	-0.00064
ζ_4	0.008*	0.009***	0.013**	0.018**	0.002704	0.00894
Panel B: Variance equation						
δ_0	0.175***	0.218***	0.238***	0.262***		0.314***
δ_1	0.652***	0.438***	0.493***	0.488***		0.543***
δ_2	0.489***	0.636***	0.596***	0.581***		0.554***
$\lambda_{1\text{ GLOBAL}}$	0.102***	0.096***	0.111***	0.064***		0.062***
$\lambda_{2\text{ EUROZONE}}$	0.027***	0.027***	0.036***	-0.011***		0.053***
$\lambda_{3\text{ TAPERING}}$	-0.03***	-0.05***	0.009***	-0.006***		-0.02***
$\lambda_{4\text{ SELLOFF}}$	0.009	-0.03***	-0.017**	0.015		0.056***

Note:*, ** and *** indicate that statistics are significance at the 10%, 5% and 1% level of significant respectively.

Equation 2.24 could not be estimated for the IDX-MALAYSIA dynamic correlations since there is no convergence.

The results using DCC-GARCH model for Latin American stock markets (2008-2015) are presented in Table 2.25. The coefficients are significant. The dynamic correlations obtained from DCC GARCH model are shown in Figure 2.9. There is a sharp increase in the correlation after 2008 which is consistent with the earlier studies (El Hedi et al, 2010; Aloui, 2011; Lahrech and Sylwester, 2011). On average the correlations between BOVESPA and COLCAP, COLCAP and IPC, COLCAP and IPSA, COLCAP and MARVEL and IPSA and MERVAL are less than 0.5, whereas the correlations between BOVESPA and IPSA, IPC and IPSA and IPC and MERVAL are around 0.5. These results indicate that there are diversification opportunities among these markets. However, the picture is somewhat different for BOVESPA and MERVAL and BOVESPA and IPC. For these markets the correlations are above 0.6 suggesting higher integration between them. It should be also noted that at times the correlations between BOVESPA and MERVAL and BOVESPA and IPC are as high as 0.80. These findings are also confirmed by the correlation coefficients obtained from DCC-GARCH.

Table 2.25 : DCC GARCH coefficients (2008-2015).

Coefficient	Value	Prob.
$\rho_{COLCAP-BOVESPA}$	0.352081	0.000
$\rho_{IPC-BOVESPA}$	0.644671	0.000
$\rho_{IPSA-BOVESPA}$	0.474242	0.000
$\rho_{MERVAL-BOVESPA}$	0.624091	0.000
$\rho_{IPC-COLCAP}$	0.359201	0.000
$\rho_{IPSA-COLCAP}$	0.324688	0.000
$\rho_{MERVAL-COLCAP}$	0.312071	0.000
$\rho_{IPSA-IPC}$	0.454027	0.000
$\rho_{MERVAL-IPC}$	0.535573	0.000
$\rho_{MERVAL-IPSA}$	0.421784	0.000
α	0.014527	0.000
β	0.976885	0.000
ν	8.39	0.000
LogLikelihood	-11696	
Li-McLeod(20)	521.8	0.19
Li-McLeod Squared(20)	493.85	0.54

ρ is correlation coefficient, α is ARCH term , β is GARCH term, ν is degrees of freedom for t distribution. Li-McLeod is Multivariate Portmanteau Statistics on Standardized Residuals, Li-McLeod Squared is Multivariate Portmanteau Statistics on Squared Standardized Residuals.

Figure 2.9 illustrate the pairwise conditional correlations dynamics. Two common features attract the attention. First, for the entire sample period, the conditional correlations are very volatile with some jumps over time. Second, all estimates are positive and the conditional correlations exhibit high standard deviations.

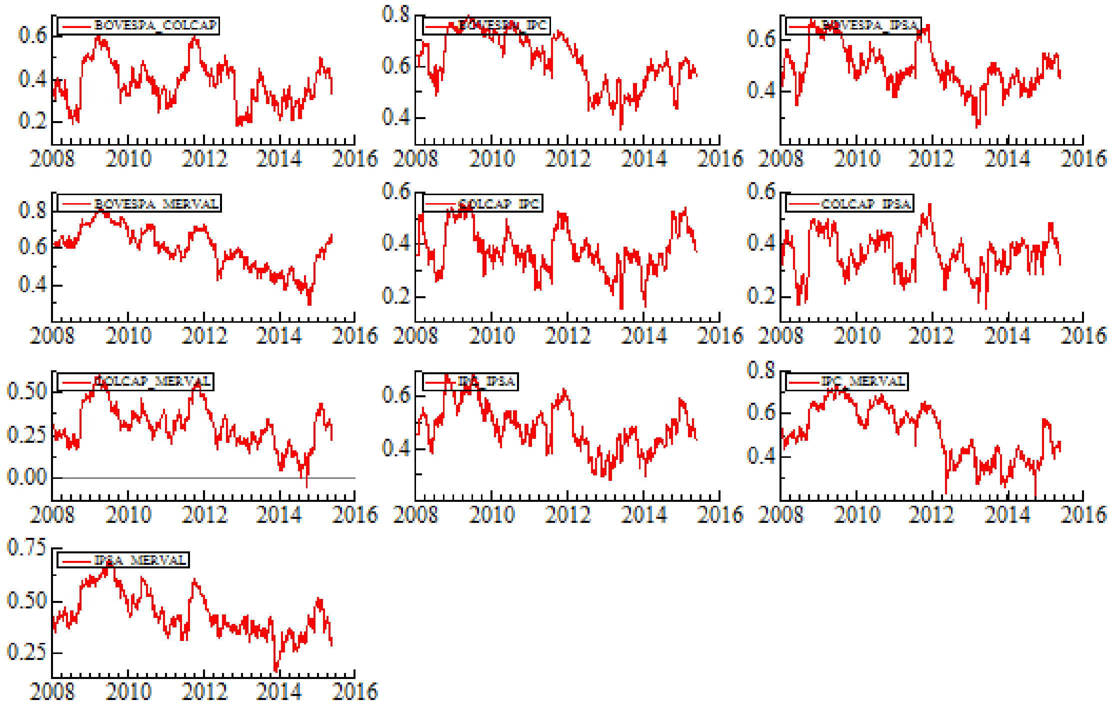

Figure 2.9 : The conditional correlation behavior over time.

Figures 2.10-2.14 illustrate the time variation of the correlations between stocks for Latin American countries: Brazil, Colombia, Mexico, Chile, and Argentina. These pairwise stock markets correlation estimates display a quite similar pattern over the sample period. Starting from September 2008 up to the beginning of May 2009, these conditional correlations increase varying within limits from 0.68 to 0.81 for the pairwise (Argentina, Brazil) and from 0.19 to 0.56 for (Argentina, Chile). A similar pattern is observed for the other stock market pairwise. The conditional correlations are rather heterogeneous until the beginning of 2013 and become more homogeneous during the period 2013-2014. The countries Colombia and Mexico contribute to this heterogeneity. A different evolution of the pairwise stock market correlation represents Argentina and Colombia. The time varying correlations between Argentina and Colombia become negative in the last week of September 2014 and then increase until the beginning of the year 2015. In addition, at the end of 2013, the conditional correlations suddenly dropped and then began to rise. This result may be explained by the fact that the Fed announcement of tapering decision on 18th of December, 2013. It would reduce its purchases of bonds and other financial assets from banks beginning in January 2014. Since tapering basically indicates the end of easy money in financial markets, emerging economies especially the Latin American have been affected by this decision.

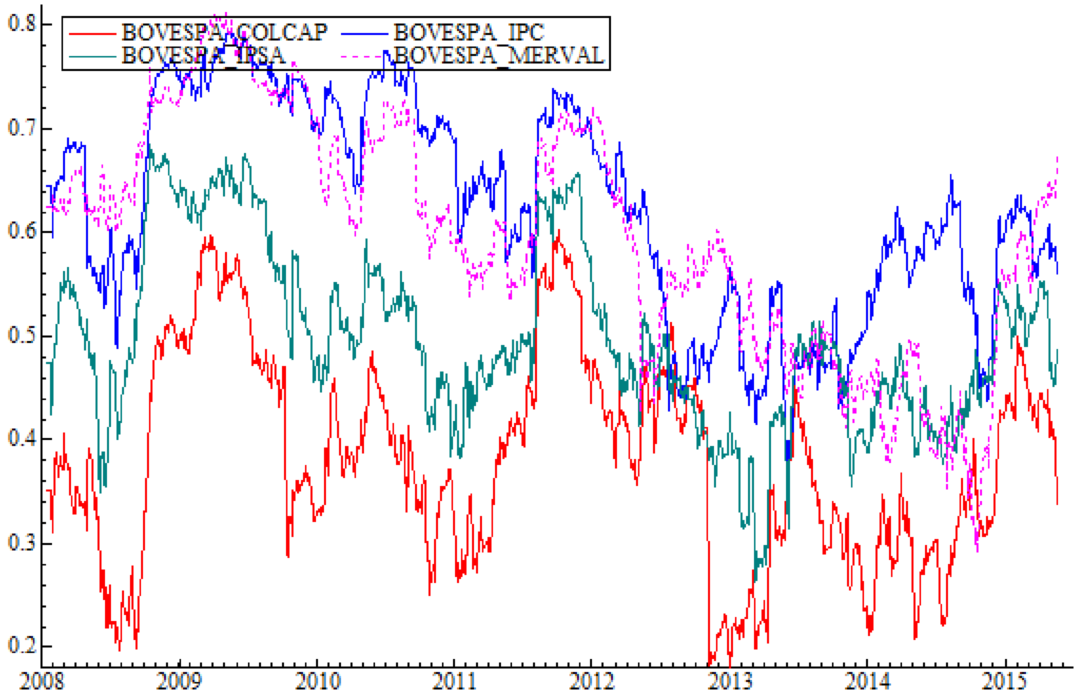

Figure 2.10 : Time varying correlations (DCC Estimates).

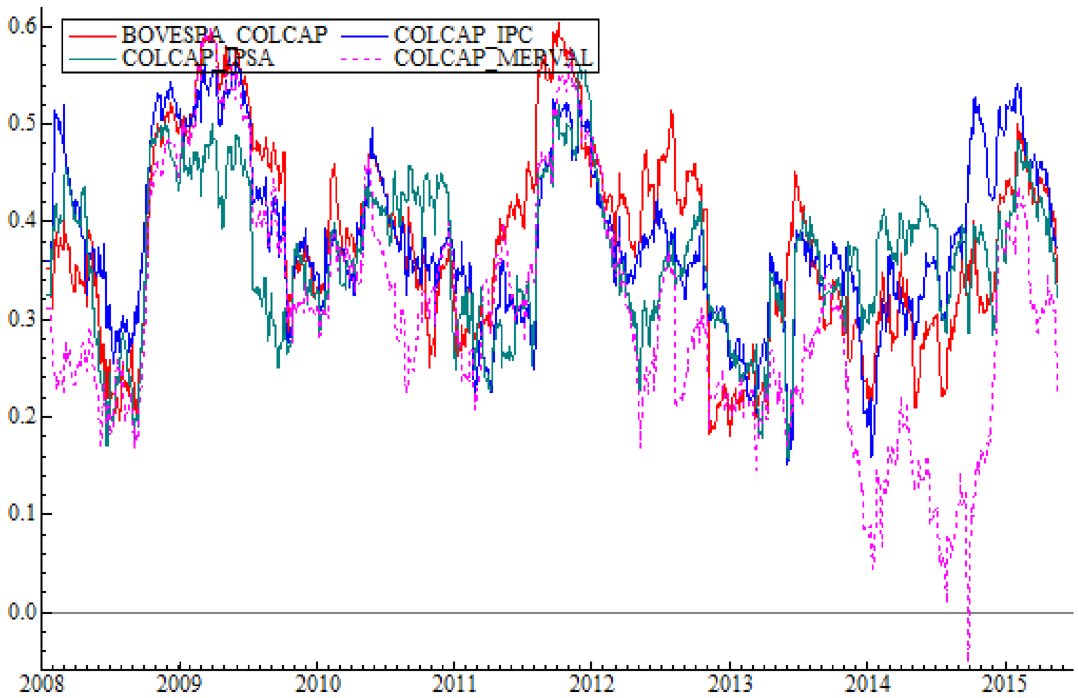

Figure 2.11 : Time varying correlations (DCC Estimates).

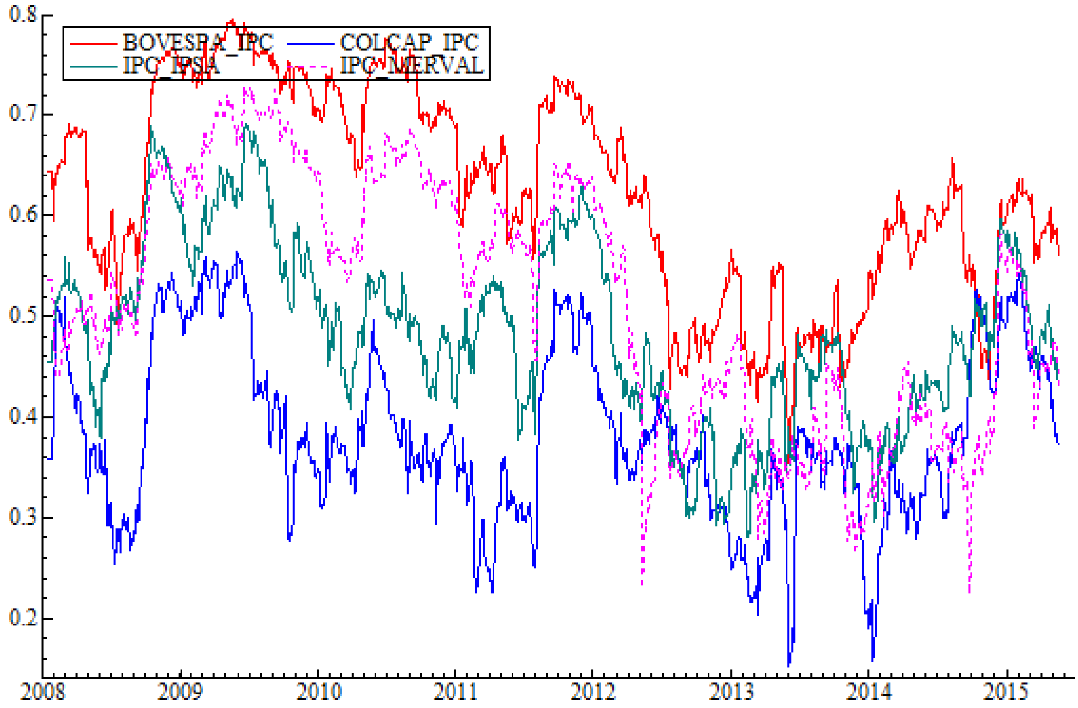

Figure 2.12 : Time varying correlations (DCC Estimates).

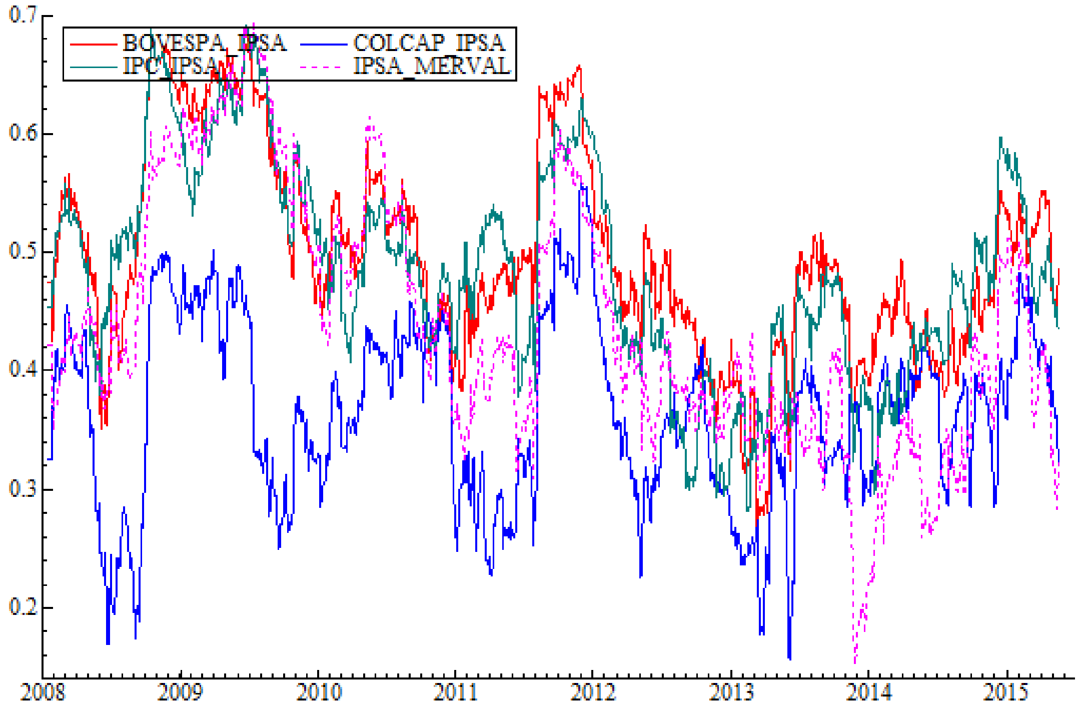

Figure 2.13 : Time varying correlations (DCC Estimates).

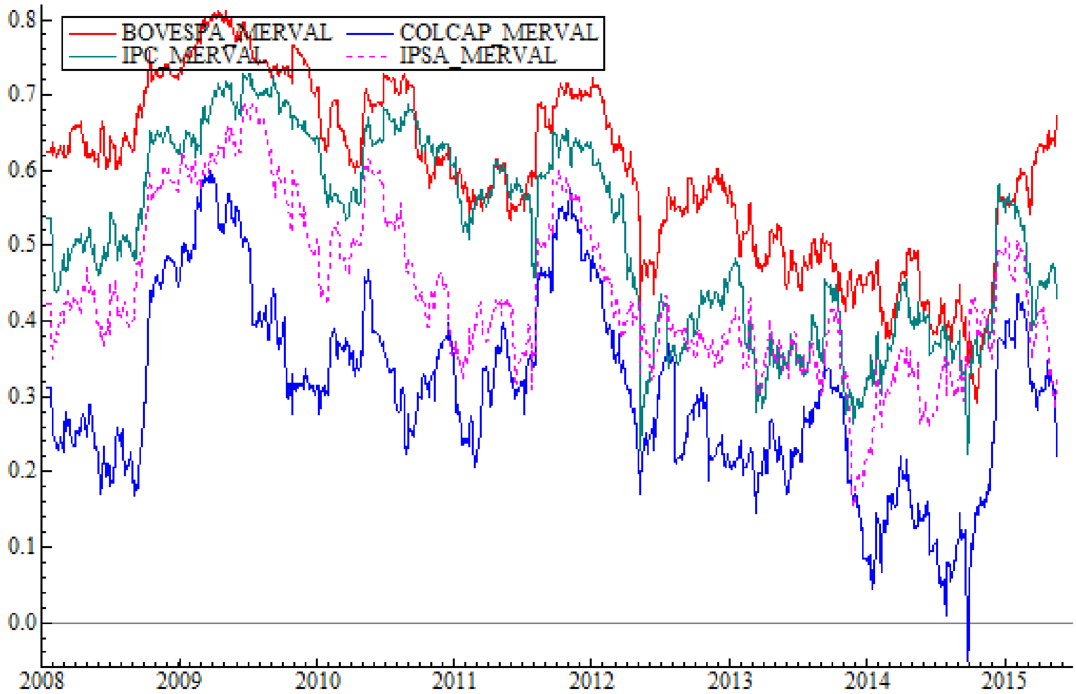

Figure 2.14 : Time varying correlations (DCC Estimates).

The AR(1)-DCC-FIAPARCH results (2002-2016) for Latin American stock markets are presented in Table 2.26. The coefficients are significant except for the market pairs of MERVAL and the others. We can see the importance of the chosen time interval of data set when we analyze dynamic conditional correlations. The results of these two analysis in Latin American countries are different from each other depending on time range.

Table 2.26 : AR(1)-DCC-FIAPARCH coefficients (2002-2016).

Coefficient	Value	Prob.
ρ IPC – BOVESPA	0.451510	0.000
ρ IPSA – BOVESPA	0.381831	0.000
ρ MERVAL - BOVESPA	0.201826	0.4243
ρ IPSA – IPC	0.366661	0.000
ρ MERVAL – IPC	0.226043	0.2268
ρ MERVAL – IPSA	0.13918	0.3832
α	0.007381	0.000
β	0.992319	0.000
ν	8.85	0.000
LogLikelihood	-21911.3	
Li-McLeod(50)	810.7	0.378
Li-McLeod Squared(50)	819.0	0.294

The dynamic correlations obtained from AR(1)-DCC-FIAPARCH model are shown in Figure 2.15-2.16. The dynamic correlations among all Latin American countries begin to rise in 2006 and this increase lasts to 2012, after then cross-market linkages fall. On average the correlations among all of the Latin American markets are less than 0.5. However, the picture is somewhat different for the period of 2006-2012. During this period the correlations are above 0.6 suggesting higher integration between them. It should be also noted that at times the correlations between BOVESPA and MERVAL and BOVESPA and IPC are as high as 0.75, 0.80. The conditional correlations are rather heterogeneous until the beginning of 2012 and become more homogeneous during the period 2012-2015. This homogeneity was originated from important initiatives to promote financial integration within Latin America. On April 28th 2011, Chile, Colombia, Mexico and Peru constituted the Pacific Alliance (PA) which aims regional integration. On July 2, 2015 by issuing the Paracas Declaration they reaffirmed their commitment to foster market integration between their countries (Werner, 2016). At the same time, the Integrated Latin America Market (MILA) purposes to integrate securities trading in the four member countries of the Pacific Alliance.

At the end of 2013, the conditional correlations suddenly dropped and began to rise after 2015. As mentioned previously emerging economies especially the Latin American have been affected by tapering decision which basically indicates the end of easy money in financial markets.

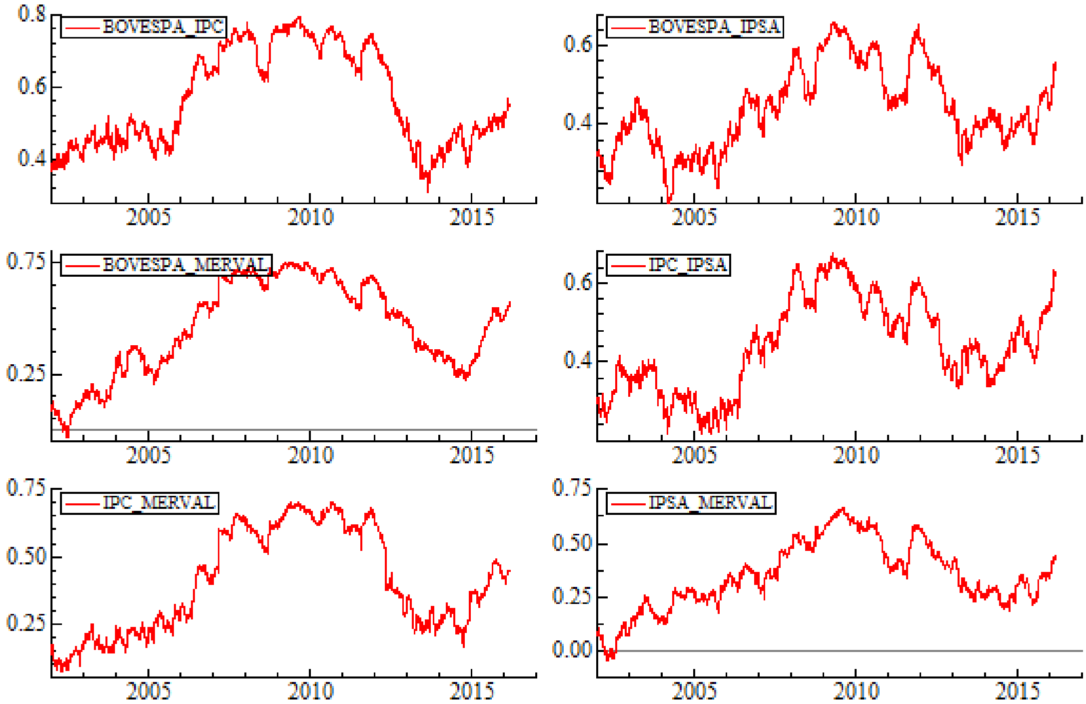

Figure 2.15 : Dynamic Conditional Correlations of Latin American countries stock returns during 2002-2016 (separately).

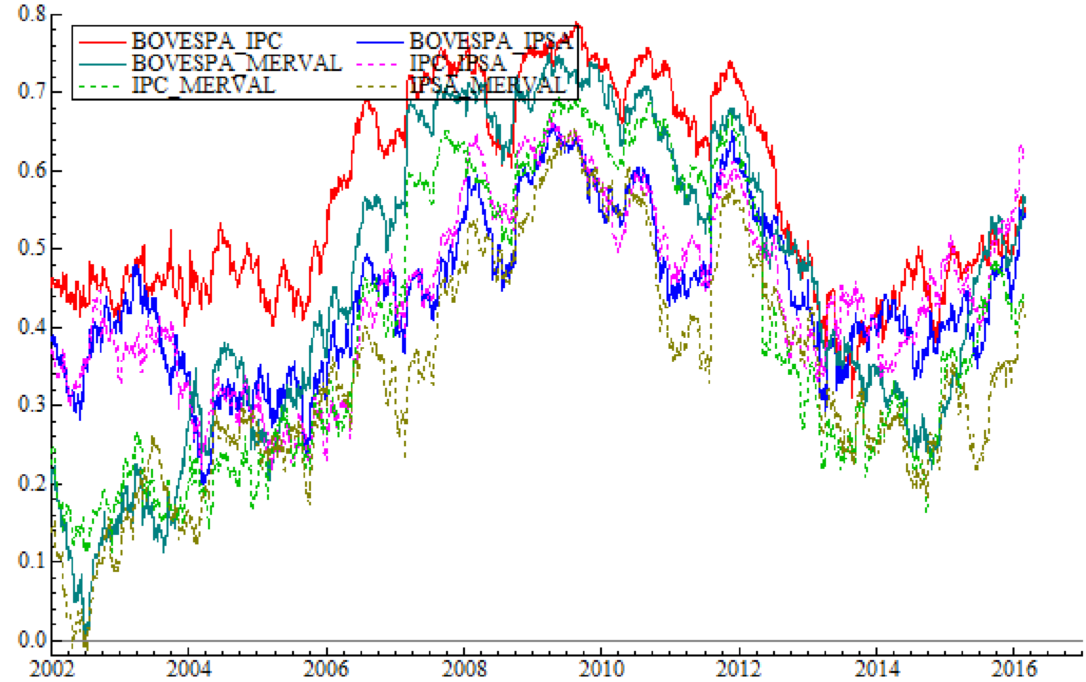

Figure 2.16 : Dynamic Conditional Correlations of Latin American countries stock returns during 2002-2016.

Table 2.27 shows the estimation results of the inclusion of dummy variables on the conditional correlations between the Latin American stock markets. The evidence shows that none of the dummies in the mean equation is statistically significant, except selloff dummy. This indicate that the correlations during the crisis periods are not significantly different from that of the normal period. On the other hand, we may infer from slightly positive and significant coefficient of stock market selloff that the dynamic conditional correlations increase during this event.

With regard to the variance equations in Panel B, the majority of all coefficients are statistically significant. Especially, coefficients of global crisis and Eurozone dummy are higher than the others. The evidence shows that global and Eurozone crisis have positive impact on the DCCs, implying that the exogenous shifts led to a rise in the volatility of the correlations between Latin American stock markets. This finding supports the hypothesis of the contagion effect. On the other hand, during tapering the coefficient λ_3 is statistically significant and negative, indicating that the tapering led to a reduction in the volatility of the dynamic correlations between the Latin American stock markets.

Table 2.27 : Impact of financial crisis on dynamic correlations.

	BOVESPA-IPC	BOVESPA-IPSA	BOVESPA-MERVAL	IPC-MERVAL	IPSA-MERVAL	IPC-IPSA
Panel A: Mean equation						
C_0	0.00072	0.001***	0.000567	0.000605	0.0009***	0.001**
ψ	0.99***	0.99***	0.999***	0.99***	0.99***	0.99***
ζ_1	0.000214	0.0007**	0.000197	0.000387	0.0009***	0.0006*
ζ_2	-4.60E-04	-4.60E-05	-0.000745	-0.000162	0.000275	-0.0004
ζ_3	-2.23E-05	-0.000266	-0.0007**	-0.000573	-0.000585	-0.0001
ζ_4	0.002**	0.005*	0.004*	0.004***	0.009***	0.004**
Panel B: Variance equation						
δ_0	0.473***	0.453***	0.427***	0.241***	0.268***	
δ_1	0.488***	0.57***	0.618***	0.654***	0.58***	
δ_2	0.564***	0.5***	0.441***	0.441***	0.485***	
$\lambda_{1\ \text{GLOBAL}}$	0.282***	0.038***	0.283***	0.37***	0.261***	
$\lambda_{2\ \text{EUROZONE}}$	0.278***	0.103***	0.277***	0.427***	0.335***	
$\lambda_{3\ \text{TAPERING}}$	-0.036***	-0.032***	-0.116***	0.0008	-0.06***	
$\lambda_{4\ \text{SELLOFF}}$	0.001	-0.03***	0.048***	0.128***	0.013**	

Note:*, ** and *** indicate that statistics are significance at the 10%, 5% and 1% level of significant respectively.

Equation 2.24 could not be estimated for the IPC-IPSA dynamic correlations since there is no convergence.

2.6 Conclusion

This dissertation investigates the volatility spillovers among stock markets in developed and emerging countries spanning the period from 01/01/2002 to 29/02/2016. A multivariate DCC-GARCH model for developed stock markets, AR(1)-DCC-FIGARCH model for Asian stock markets and AR(1)-DCC-FIAPARCH model for Latin American markets were estimated. As I mentioned before, to analyze the volatility spillovers among the stock markets, taken into account the breaks in variance. Therefore, before estimating DCC-GARCH model, first structural breaks tests in variance were proceeded. Only the structural break points for Latin American countries were found statistically significant and dummy variables for these variance break dates were constituted. Then, DCC-GARCH model was estimated with these dummy variables in variance. While volatility transmission mechanism was being investigated, long memory property and asymmetry effect were being considered for all markets. Hence, the long memory property in squared return of all market indices was analyzed by using test statistics of Hurst-Mandelbrot R/S, Lo R/S, GPH and GSP. Due to the significant long memory tests results, the most appropriate DCC-GARCH model was estimated which take into account long memory property and asymmetry effect. The most fitting model for stock markets in developed countries is AR(1)-DCC-FIGARCH(1,d,1) model under the Student-t distributed innovations. Results indicated that volatility processes are persistent over time for all developed stock markets.

Dealing with developing stock markets, countries were classified into two groups according to geographical area such as Asian and Latin American. And one may suggest that the most appropriate estimation method for these developing countries is AR(1)-DCC-FIAPARCH (1,d,1) with Student-t distribution. According to findings, leverage effect coefficients (γ) are positive and statistically significant in all cases. Therefore, one may conclude that negative shocks are more effective on volatility than positive shocks of same magnitude. Moreover, the evidence shows that all volatility processes are persistent over time.

On the other hand, the dynamic conditional correlations among the pairs of countries were examined. Dynamic conditional correlations from fractionally integrated process were obtained which consider long memory property in volatility. Considering developed markets, the dynamic conditional correlations between S&P 500 and FTSE

100 indices are the highest. Dynamic conditional correlations among S&P 500 reveals strong correlations with FTSE 100. For these markets the correlations are above 0.5 suggesting higher integration between them. On the other hand, on average the correlations between NIKKEI 225 and other markets are less than 0.24. This result indicates that there is portfolio diversification opportunities between NIKKEI 225 and other developed markets.

However, the results show that correlations between NIKKEI 225 and FTSE 100 begin to increase in 2007 prior to the United States (U.S.) subprime mortgage crisis and end of 2008 it reaches its highest level when several major financial institutions collapsed in September 2008. In addition, in August 2015 correlation between NIKKEI 225 and FTSE 100, and NIKKEI 225 and S&P 500 suddenly increase. This increase arises from the 2015–16 stock market selloff which began in the United States on August 18, 2015. After the August 11 announcement of a change in the exchange rate regime of the Renminbi, Chinese equities fell sharply on August 24, 2015. And also this situation affected the U.S. and European stock markets adversely.

According to the definition of contagion as an increase of the correlation coefficient in a crisis period compared to a benchmark period, it can be seen that these findings signal financial contagion effects between Japan and United Kingdom, and United States.

On average the correlations among Asian stock markets are less than 0.5, whereas the correlations between Malaysia and Indonesia are around 0.4. These results indicate that Asian markets are weakly correlated. Crisis dummies have a significant and positive impact on the dynamic conditional correlations between Asian stock markets, supporting the hypothesis of contagion effect. On the other hand, during tapering the coefficient of tapering dummy is statistically significant and negative, indicating that the tapering led to a reduction in the volatility of the dynamic correlations between the Asian stock markets.

However, the picture is somewhat different for BOVESPA and MERVAL and BOVESPA and IPC. For these markets the correlations are above 0.6 suggesting higher integration between them. The results suggest that diversification opportunities does not seem to exist between BOVESPA and MERVAL, and BOVESPA and IPC. From the estimation result of AR(1)-DCC-FIAPARCH model for Latin American stock markets during the period 2002-2016, one may observe the coefficients for DCC are significant except for the market pairs of MERVAL and the others.

Moreover, none of the crisis dummies in the mean equation of dynamic conditional correlations between Latin American markets is statistically significant, except selloff dummy. On the other hand, we may infer from slightly positive and significant coefficient of stock market selloff that the dynamic conditional correlations increase during this event.

With regard to the variance equations, the evidence shows that global and Eurozone crisis have positive impact on the DCCs, implying that the exogenous shifts led to a rise in the volatility of the correlations between Latin American stock markets. This finding supports the hypothesis of the contagion effect. On the other hand, during tapering the coefficient λ_3 is statistically significant and negative, indicating that the tapering led to a reduction in the volatility of the dynamic correlations between the Latin American stock markets.

3. FINANCIAL CONTAGION AND FLIGHT TO QUALITY EFFECTS IN STOCK MARKETS AND U.S. BOND MARKET

3.1 Introduction

In the process of globalization capital markets are integrated with each other in consequence of increasing transnational corporations, developing international trade network, and development of political and economic unions like European Union. However increased integration plays an opposing role in the dispersion of risks. Thereby, the analysis of diversification and dispersion of risk is an important issue for both investors and researchers. In this respect the aim of this essay is to examine the mechanisms of market risks spillovers.

Empirically evaluation of these spillovers is an important issue. Theoretically propagation of shocks can be divided into two groups. One of them is crisis-contingent theories which explain why market cross correlations increase after a shock. The transmission mechanism behind the crisis contingent theories apart from multiple equilibria based on investors' expectations. When a shock hits one country, investors could believe that the equilibrium of other country shift from a good to a bad state. This psychological situation transmit the shock during crisis periods rather than normal periods. The other theory is endogenous liquidity shocks. This theory reveals that when financial disaster in one country occurs then the other country could be affected from this crisis. Investors who lose a lot of liquidity are forced into selling their assets in other country and have to reconstitute their portfolio. The last one is political contagion which affects the exchange rate regime (Forbes and Rigobon, 2001).

However with regard to noncrisis-contingent theories the spillovers of shocks is based on the available financial and commercial relationships. The empirically literature testing if spillover exist during a crises period draws an inference from significant and short lived increase in cross correlation between markets. Early work was done by King and Wadhwani (1990); Calvo and Reinhart (1995); Baig and Goldfajn (1999).

First, Forbes and Rigobon (2002) demonstrated that correlation coefficients are conditional on market volatility. Put differently, heteroscedasticity in market returns can result estimates of cross-market correlation coefficients to be biased upward after a crisis. To adjust for this potential bias they used the unconditional correlation rather than the conditional one. And they found that there was not any increase in unconditional correlation coefficients during the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. market crash. They ascertain that there is a high level of market comovement in all periods, namely interdependence. On the other hand, correlation between two markets does not report the direction of the contagion. Because of this reason, Granger causality approach is more appropriate to measure spillovers.

Furthermore causality does not separate interdependence from contagion. Interdependence can be defined as a long run causality between markets. In contrast to interdependence, contagion comes in sight in the short run especially in the period of financial crisis. Therefore one should deal with the extreme left tail of the distribution in order to test for contagion (Hartmann et al, 2004). Taking the whole distribution into consideration to measure contagion would change the results. This new technique enables to test for causality for the whole distribution as well as for specific percentiles of the distribution.

More explicitly the goal of this dissertation is to determine whether there is a possibility of risk diversification between markets by determining the causal relations especially among the tail of the distributions with the help of Granger causality analysis, and by classifying the risk spillovers between Turkey and the other stock markets and also between stock markets and U.S. bond market as financial contagion, flight to quality or flight from quality.

Granger causality test is employed not only for the mean and variance but also for the other moments such as quantile pairs of (0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8) and (0.8, 1) of the stock market indices. This Granger causality test in moments account for the volatility asymmetry between markets with EGARCH specifications and differentiate between contagion and interdependence. Interdependence is a long term phenomenon and takes place during normal periods, for this reason consider the center of the distribution. Otherwise contagion occurs in the short run and be measurable only with causality in the left tails of the distribution. And causality from the left tail of a given equity index distribution to the right tail of bond return distribution points to the flight to quality. By the same token, causality from the left tail of bond return distribution to the right tail of stock return distribution may be interpreted as flight from quality effect. Therefore, by means of Granger causality tests risk spillovers across markets are categorized as interdependence, contagion, flight to quality or flight from quality. This study attempts to provide important information to the investors who want to diversify and reduce the risks with the help of this classification and may be a guide for policy makers and researchers.

3.2 Literature Review

Increasing volatility and importance of risk spillovers among the financial markets have extended the studies focusing on controlling and monitoring financial risk. Economic agents follow risk protection models as well as the probability of major downward market movements in order to implement robust policies. In these periods of high volatility and extreme market movements it has been seen that a large amount of capital changes hands.

Previous studies on volatility have been widely focused on risk measurement and volatility spillovers. In this context, Cheung and Ng (1990) found that there is a causal relationship between the conditional variances of financial asset returns. Engle et al. (1990) investigated the information flow from one market to another in their study of Yen/Dollar exchange rate.

Engle and Susmel (1993) explored whether the two different international stock markets are following the same volatility process by benefiting from the time varying nature of stock return variances. In their studies, they emphasized that time-dependent volatilities in some international stock markets are similar.

Hamao et al. (1990) examined the price and price volatility dependence among the three main international stock markets. They have worked with daily opening and closing data of stock markets in Tokyo, London and New York. In their studies, they used ARCH-type models to examine the relationship between prices and have identified the existence of price volatility from New York to Tokyo, from London to Tokyo and from New York to London.

Similarly, King and Wadhwani (1990) addressed an issue of simultaneous decline of almost all stock markets in October 1987. In their study on Tokyo, London, and New York financial markets, they emphasized that there is a widespread spillover effects among markets. This study pointed to the existence of spillover effects among markets which are in different economic structures.

King et al. (1994) estimated a multivariate factor model with the national stock exchange index data of 16 countries and investigated the integration of capital markets. They show that mostly unobservable variables cause to time-dependent covariance structures of stocks.

Lin et al. (1994) dealt with the Tokyo and New York markets and investigated the correlation between stock market index returns and volatility. The study of Hong's (2001) in the area of volatility spillover proposes tests which are based on the weighted sum of squared sample cross-correlations between two squared standardized residuals. In this test, a more flexible weighting method was developed for each lag by using all sample cross correlations, unlike the test of Cheung and Ng (1996) and the regression-based test of Granger (1969). Granger causality between the two currencies was investigated by using the weekly data of Dollar/Mark and Dollar/Yen exchange rates. He emphasized that German Mark's past volatility changes are the reason for the current volatility change in the Japanese Yen, but that there is no relationship in the opposite direction.

In their article, Diebold and Yılmaz (2009) developed accurate and separate measures of return and volatility spillovers. From January 1992 to November 2007 they investigated daily nominal local currency stock market indexes of seven developed stock markets (US, UK, France, Germany, Hong Kong, Japan and Australia) and twelve emerging markets (Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico and Turkey). They examined both non-crisis and crisis episodes involving trends as well as bursts in spillovers. Particularly, in the analysis of nineteen global equity markets, they showed evidence of divergent behavior in the dynamics of return spillovers vs. volatility spillovers. They demonstrated that return spillovers display a gently increasing trend but no bursts, link with gradually increasing financial market integration, whereas volatility spillovers exhibit no trend but clear bursts identifying with crisis events.

Henry et al. (2007) investigated the spillovers of returns and volatility in the stock market using causality tests in mean and variance by Cheung and Ng (1996) for eight South Asian countries (Indonesia, Philippines, South Korea, Hong-Kong, Japan, Malaysia, Singapore, Thailand) and revealed that Thailand has momentarily binary volatility spillover effects on Indonesia.

In their research, Okur and Çevik (2013), who deal with financial markets in Turkey, analyzed the spillover of volatility between the futures index and the stock indices. Therefore, they used the causality test in variance which is put forward by Hong (2001) and Hafner and Herwartz (2006). According to their findings, spot market is Granger cause of the futures market.

In their study, Taşdemir and Yalama (2014) examined volatility transmissions between Turkish and Brazilian markets. According to their findings they concluded that there is a volatility spillover from São Paulo's stock market to Turkish stock market. In addition, they emphasized volatility transmissions from Turkey to Brazil during the periods of financial crisis.

Using GJR-GARCH method, Korkmaz and Çevik (2009) analyzed the effects of volatility index of USA (VIX) on the 15 developing countries' stock markets. They concluded that there exist leverage effect in the conditional volatility of the developing stock markets and bad news that come into markets increase much more volatility. They noted that VIX affects the stock markets of Argentine, Brazil, Mexico, Chile, Peru, Hungary, Poland, Turkey, Malaysia, Thailand and Indonesia and increases their volatility.

Granger causality analysis (Granger, 1969), which is used mostly in mean and for economic modelling, reveals causality between two random variables. Pierce and Haugh (1977) proposed two stages procedure in order to test causality between two variables. In the first stage, each of the variables are transformed in such a way that they have a constant conditional mean and variance during sampling period, using procedures of logarithm and differencing. Afterwards, an ARMA model has been estimated and causality has been tested by cross correlations. Using likelihood ratio test, Newbold (1982) tested causality in bivariate ARMA model.

Otherwise, Geweke (1982) determined linear dependency in his study. In the light of Granger causality analysis, Boudjellaba et al, (1992, 1994) developed a test for vector autoregressive moving average (VARMA) model. Dufour and Taamouti (2010) investigated two way causality by developing parametric and nonparametric technics. They identified parametric measures by impulse response coefficients of vector moving averages (VMA). In their researches they improved an approach based on simulation.

For financial time series, in the context of Granger et al (1986), causality in variance tests were developed in order to examine contagion effect of financial shocks. These tests were improved by Cheung and Ng (1996), Hong (2001), Kanas and Kouretas (2002), and Hafner and Herwartz (2004). Kanas and Kouretas (2002) investigated causality in mean and in variance between foreign exchange of four Latin American countries against U.S. Dollar during the period of 1976-1993. Accordingly, using EGARCH-M model they examined movements of foreign exchange of Argentine, Brazil, Chile, and Mexico against US Dollar. Then, they tested volatility contagion by getting help of Cheung and Ng (1996)'s approach. Hafner and Herwartz (2006) examined causality in variance between financial returns by using Lagrange Multiplier Test. In other study, Hafner and Herwartz (2008) brought forward an approach based on a multivariate GARCH model and advanced a Wald type test for testing causal relationships. They emphasized that Wald test is powerful against misspecifications of log likelihood function.

Granger causality is vested with a predictive nature for the market, which is subject to analysis, rather than a causal relationship. Recently, the Granger causality approach in quantiles has been developed for fat tailed, asymmetric, and nonlinear distributions (Lee and Yang, 2012; Jeong et al, 2012). In these non-Gaussian distributions, quantiles are utilized in order to evaluate different information in the tails and the center. Lee and Yang (2012) developed the Granger causality test in quantiles to investigate the causality relationship between money and income using the conditional predictive ability test suggested by Giacomini and White (2006). Jeong et al, (2012) tested the causality relationship among oil prices, exchange rates and gold prices with a nonparametric test approach by quantile causality testing.

Hong et al, (2009) have contributed to the current literature by testing causality in tails. In finance literature, left tail probability associated with downward extreme market movements (Embrechts et al, 1997; Hong et al, 2009). In addition, quantiles, which are an element of Value at Risk (VaR) in finance theory, are mostly used as a measure of risk (Duffie and Pan, 1997; Engle and Manganelli, 2004). Causality test in risk of Hong et al. (2009) is based on the GARCH model and the conditional quantile model. Hong et al. (2009) pointed out that the Granger causality test in risk shows that whether a great deal of risk in a market in the past could be a messenger of a big risk in another market that could come in existence in the future.

Bouezmarni et al. (2012) performed Granger causality in distribution with regard to the conditional dependency which comes from Copula theory. Su and White (2012) implemented Granger causality in quantiles for continuous values between (0,1) interval of quantiles using conditional independence specification test.

Candelon et al. (2013) put forward the Granger causality test for multiple risk levels between tails of distributions by improving the testing procedure of Hong et al. (2009). Using this test for oil markets, they obtained information about this market, especially during periods of excessive price movements. According to their findings, the integration between petroleum markets shows a tendency to decrease in the periods of extreme price activity.

In their study, Balcılar et al. (2014) investigated the causal relationship between agricultural prices and petroleum price spanning the period from 2005 to 2014. In a similar manner Jeong et al. (2012), they took advantage of causality in quantile test. According to their findings, the effect of petroleum price on agricultural product prices vary across different quantiles of conditional distribution. They suggested that the effect on tails is lower than the whole distribution. In addition, they emphasized that Granger causality tests fail due to the nonlinear dependency between petroleum and agricultural prices.

Using a nonparametric quantile causality test, Balcılar et al. (2016) analyzed return and volatility of 16 developed and developing countries foreign exchanges against U.S. dollar for the period from 1999 to 2012. Quantile causality approach enables them to test causality not only in mean but also causality that may exist in tails of distribution. Besides they investigated volatility spillovers by testing causality in variance.

In a recent study, Candelon and Tokpavi (2015) tested Granger causality in whole distribution of two time series. This approach was derived from Portmanteau test of Bouhaddioui and Roy (2006) and very useful due to its ability to test causality between various areas of distribution.

Corsi et al, (2015) analyzed the flight to quality phenomenon of financial institutions. They examined risk spillover by using bond return of 36 countries and stock market returns of 33 banks. Considering this study, during the European crisis banks have followed quality at bond market.

Chen (2016) developed a generalized parametric test which is derived from asymptotic method for full-sample moment test of Newey (1985) and Tauchen (1985). Namely, without assumption of independence, this cross correlation test reveals that Box Pierce type tests are applicable to various moments. This approach differs from sup-Wald test conducted by Chuang et al, (2009) and quantile causality test of Jeong et al, (2012) and is named as Granger causality in moments.

In their researches Eichengreen et al. (2001) concluded that there exist flight to quality from emerging markets to U.S. Treasury securities along the sample covering the period of 1991-1999 during the three crises period Mexican, Asian and Russian. Researchers dealt with 10 years yield of U.S. Treasury bond and the difference between 10-year and 1-year U.S. Treasury rates as indicators of the international credit market conditions. They asserted that the flight to quality considerably influence the region in which the crisis originates. Besides, they found less evidence of flight to quality impact on maturities. They further suggested that investors prefer short-term to long-term instruments during flight to quality period.

Using a sample of the Dow Jones Corporate 02 Years Bond Index (DJBI02) versus the Dow Jones Industrial Average (Dow 30 Industrial Stock Price Index (DJSI)), and the Dow Jones Corporate 30 Years Bond (DJBI30) Index versus the Dow 30 Industrial Stock Price Index, Gonzalo and Olmo (2005) investigated relationship between the stock and bond prices for the period of 1997-2004. They stated that there exist flight to quality feature in the DJBI02 and DJSI pair of indexes. Therefore they emphasized that bond returns are negatively related to the stock returns in the period of stress. However, Gonzalo and Olmo (2005) don’t assert any flight to quality effect between the DJBI30 and DJSI pair. Consistent with their findings DJBI02 could be evaluated as safe haven for investors flying from the financial distress.

By using the method of causality in quantile, Balcılar et al. (2017) investigated whether U.S. news on inflation and unemployment causes returns and volatility of seven emerging Asian stock markets during the period 1994 - 2014. They argued that U.S. news influence on returns and volatility of all the stock markets. They further suggested that these effects clustered around the tails of the conditional distribution of returns and volatility when they are either in falling or rising periods.

3.3 Data

In this essay, daily index values of stock exchange market indices of selected emerging and developed countries and some regional stock market indices spanning the period from 01/01/2002 to 29/02/2016 were analyzed. In order to represent regional stock markets; Standard and Poor's Europe Stock Market Index (SPEU), Standard and Poor's Asia Stock Market Index (SPAS50), and S&P Africa 40 index were used. National stock markets are represented by BIST 100 (Turkey), S&P 500 (USA), DAX-100 (Germany), FTSE-100 (UK), NIKKEI 225 (Japan), MERVAL (Argentina), BOVESPA (Brazil), IPC (Mexico), IPSA (Chile), COLCAP (Colombia), IDX (Indonesia), S&P BSE SENSEX Index (India), and KLCI (Malaysia). The data set was extracted from the Thomson and Reuters DataStream database. Table 3.1 shows the list of stock indices and their abbreviations.

Table 3.1 : List of Stock Indices.

Country	Type of Market	Stock Index
Hong Kong, Korea, Singapore, Taiwan	Major Asian markets	S&P ASIA 50
Eurozone	Eurozone market	S&P EURO
17 African countries	African market	S&P AFRICA 40
Turkey	Emerging Europe	BIST 100
US	Developed America	S&P 500
Germany	Developed Europe	DAX 100
UK	Developed Europe	FTSE 100
Japan	Developed Asia	NIKKEI 225
Argentina	Emerging America	MERVAL
Brazil	Emerging America	BOVESPA
Chile	Emerging America	IPSA
Mexico	Emerging America	IPC
Colombia	Emerging America	COLCAP
Malaysia	Emerging Asia	MALAYSIA KLCI
India	Emerging Asia	S&P BSE (SENSEX) 30
Indonesia	Emerging Asia	IDX COMPOSITE

In order to analyze flight to quality phenomenon, causal relationship between these stock markets and U.S. bond market is investigated. In this concept, daily values of

U.S. two year bond yield (USGG2YR) were examined. U.S. two year bond yield (USGG2YR) data set was extracted from the Bloomberg database.

Daily return series are calculated as log differences of price levels as follows:

$$r_t = 100 \times \left[\ln P_{i,t} - \ln P_{i,t-1} \right] \quad (3.1)$$

The price series and return series of national and regional stock indices are plotted in Figures 3.1-3.5.

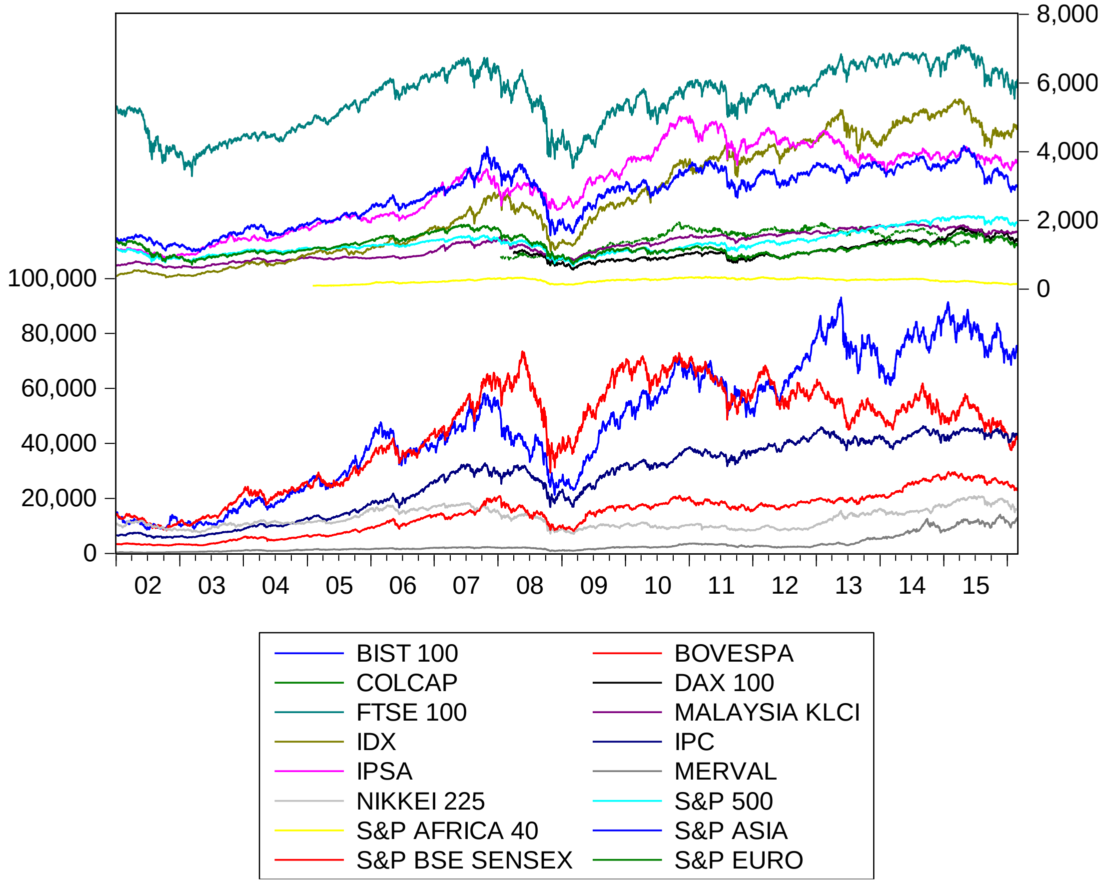

Figure 3.1 : Multiple time series plots of stock price series.

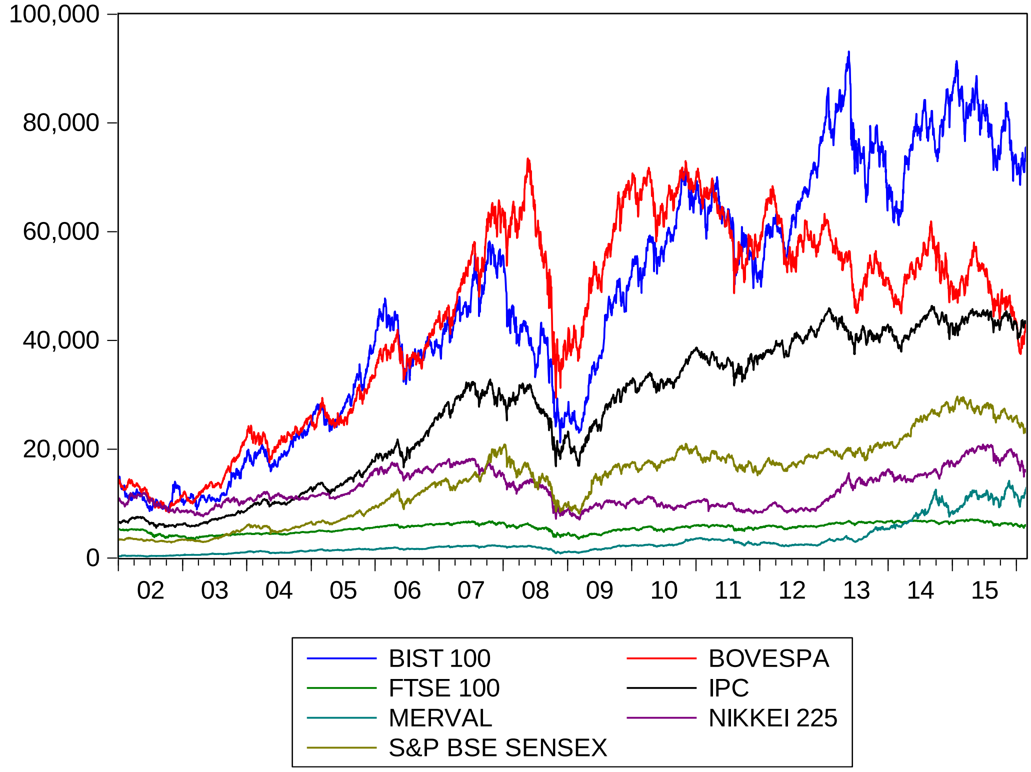

Figure 3.2 : Time series plots of stock price series.

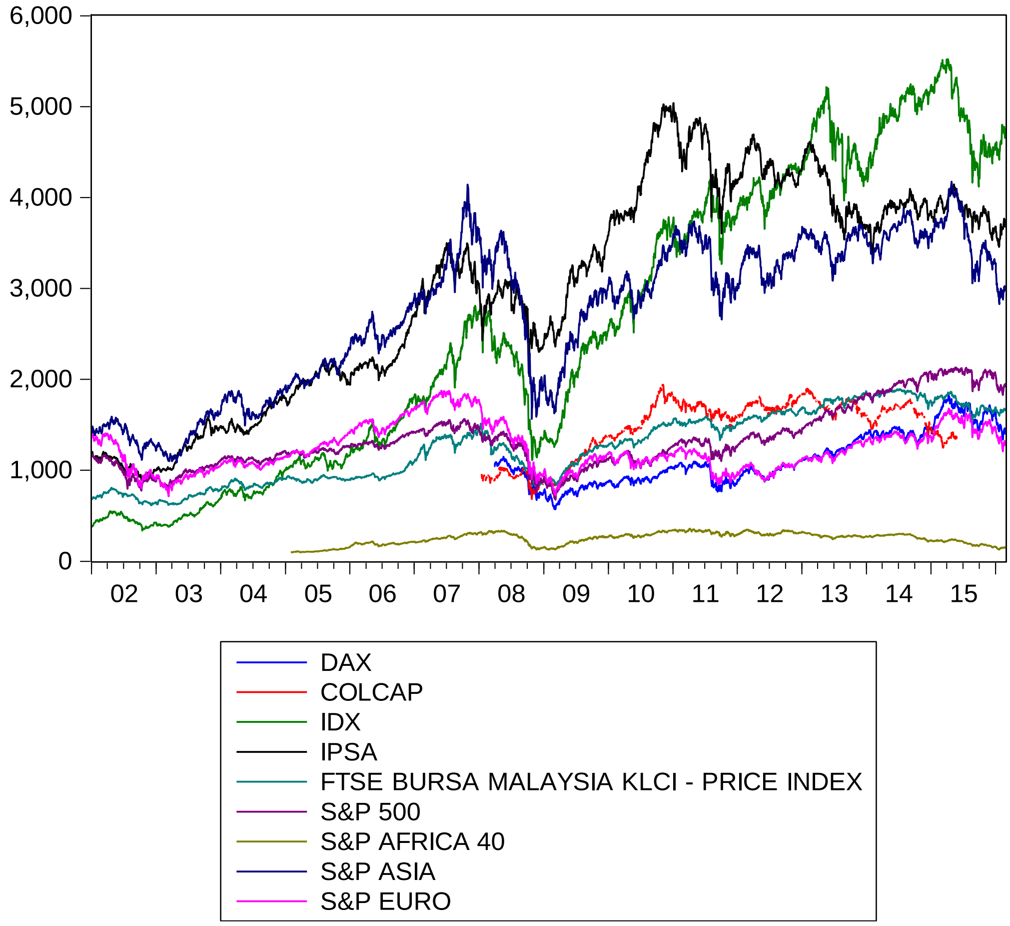

Figure 3.3 : Time series plots of stock price series.

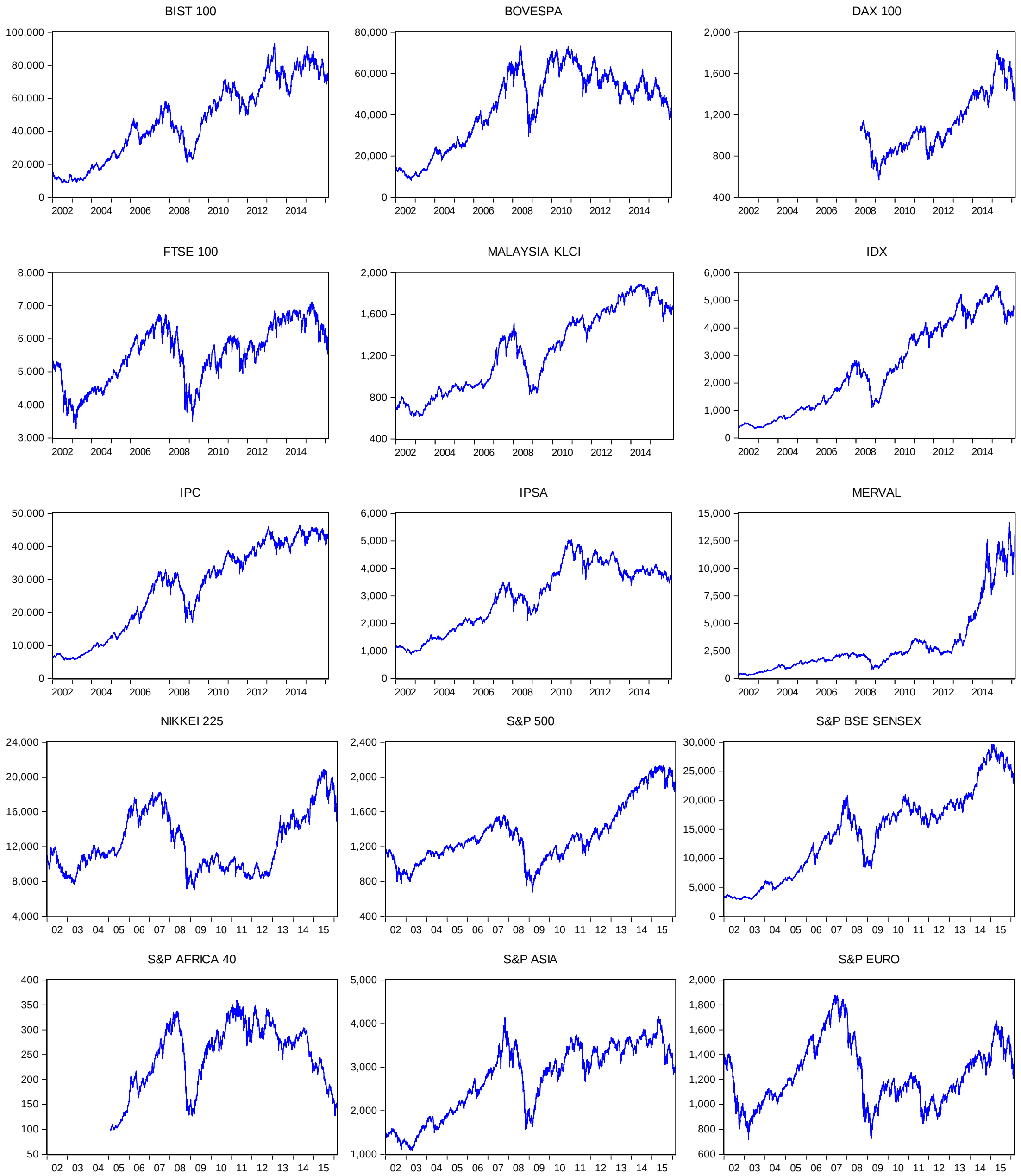

Figure 3.4 : Time series plots of stock price series.

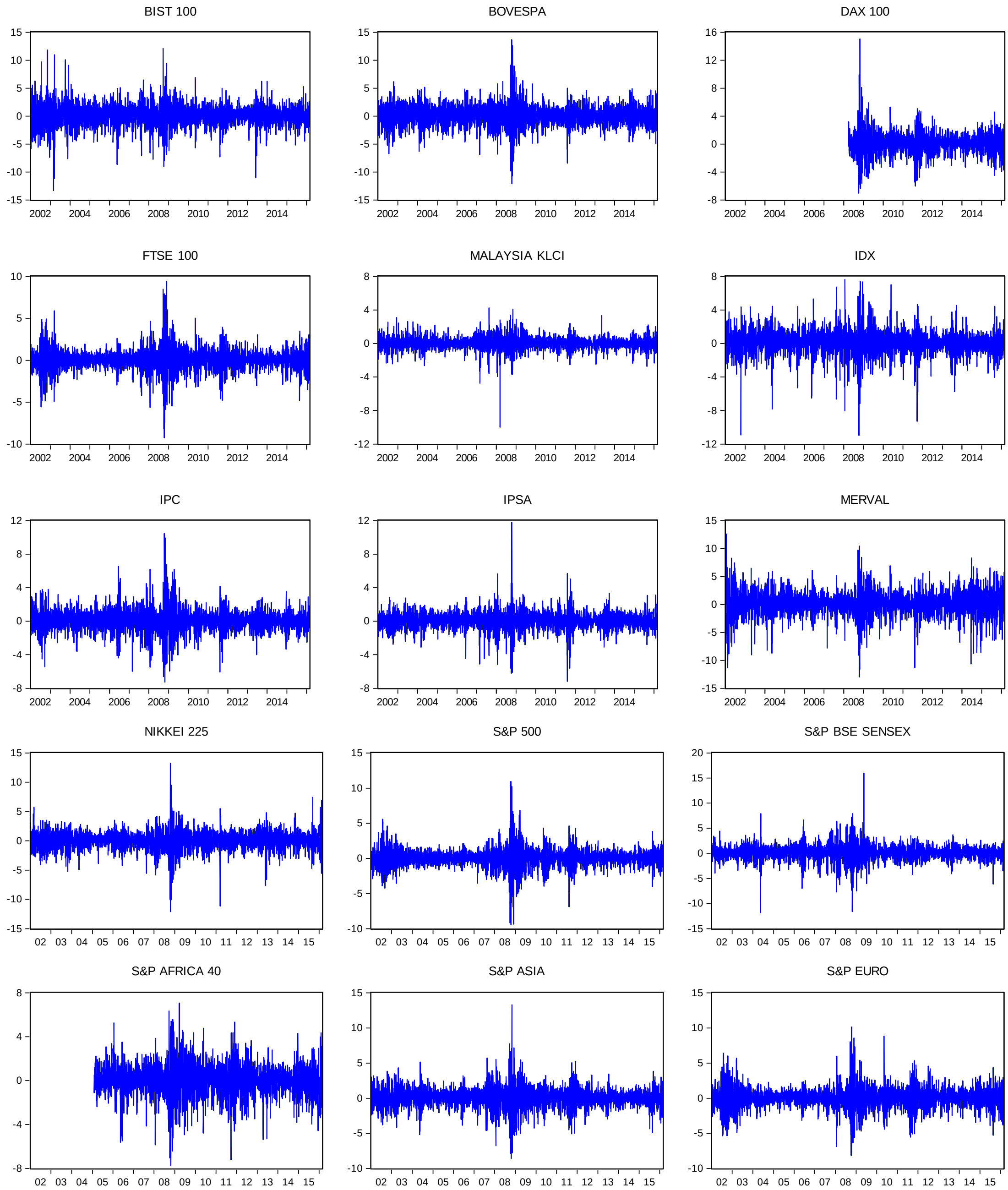

Figure 3.5 : Time series plots of stock return series.

Descriptive statistics for these return series are presented in Tables 3.2a-3.2c. As can be observed in Tables 3.2a-3.2c, stock returns have excess kurtosis (fat tails) and negative skewness. As can be seen from the Tables 3.2a-3.2c the distributions of all series are leptokurtic. Furthermore, the Ljung-Box Q (20) and Q^2 (20) statistics are significant for all raw returns and squared returns indicating presence of serial correlation and ARCH effects. In addition, based on the Jarque-Bera normality (1987) and Engle's Lagrange Multiplier ARCH (1982) test reported in Tables 3.2a-3.2c, stock return data exhibits non-normality and fits ARCH-type modeling techniques.

Table 3.2a : Descriptive statistics of return series.

	BIST_100	BOVESPA	DAX 100	FTSE_100	IDX
Mean	0.046152	0.031078	0.016063	0.004218	0.067649
Median	0.037818	0.000000	0.046385	0.002364	0.060711
Maximum	12.12721	13.67942	15.05378	9.384339	7.623121
Minimum	-13.34085	-12.09605	-7.049075	-9.265572	-10.95400
Std. Dev.	1.856294	1.743733	1.486086	1.207556	1.361725
Skewness	-0.125729	-0.062366	0.401339	-0.139326	-0.715053
Kurtosis	7.530263	7.722218	11.16460	10.05883	10.57476
Jarque-Bera	3168.607	3434.635	5793.841	7681.169	9146.065
ARCH 1-2	29.89 [0.000]	229.18 [0.000]	80.12 [0.000]	130.78 [0.000]	100.81 [0.000]
ARCH 1-5	33.30 [0.000]	125.78 [0.000]	44.44 [0.000]	122.28 [0.000]	50.76 [0.000]
ARCH 1-10	20.67 [0.000]	90.969 [0.000]	31.11 [0.000]	69.83 [0.000]	28.48 [0.000]
Q(20)	42.34 [0.000]	49.43 [0.000]	53.08 [0.000]	56.72 [0.000]	91.82 [0.000]
$Q^2(20)$	596.15 [0.000]	3102.7 [0.000]	1208.18[0.000]	2457.5 [0.000]	147.81 [0.000]
Observations	3694	3694	2066	3694	3694

Table 3.2b : Descriptive statistics of return series.

	IPC	IPSA	MERVAL	COLCAP	NIKKEI225	MALAYSIA KLCI
Mean	0.052131	0.030981	0.102688	0.021814	0.011338	0.023441
Median	0.041880	0.006231	0.023746	0.060330	0.000000	0.010344
Maximum	10.44071	11.80337	12.59611	8.731454	13.23458	4.2587
Minimum	-7.266123	-7.188170	-12.95163	-8.923.942	-12.11103	-9.9785
Std. Dev.	1.231553	0.986046	2.054744	1.184264	1.497589	0.73692
Skewness	0.073498	-0.001941	-0.341309	-0.404428	-0.440371	-0.866894
Kurtosis	9.132839	13.06443	7.284588	9.410213	10.39159	15.50074
Jarque-Bera	5792.395	15590.65	2897.275	2748.217	8528.729	24514.98
ARCH 1-2	94.47 [0.000]	87.55 [0.000]	81.22 [0.000]	275.54 [0.000]	374.4 [0.000]	71.9 [0.00]
ARCH 1-5	80.31 [0.000]	74.25 [0.000]	58.2 [0.000]	118.96 [0.000]	173.9 [0.000]	42.5 [0.00]
ARCH 1-10	58.09 [0.000]	51.73 [0.000]	29.8 [0.000]	64.642 [0.000]	94.8 [0.000]	29.33 [0.00]
Q(20)	49.88 [0.000]	113.8 [0.000]	43.5 [0.000]	55.992 [0.000]	12.7 [0.000]	45.5 [0.00]
$Q^2(20)$	2353.7 [0.000]	962.3 [0.000]	824.8 [0.000]	1431.7 [0.000]	2463.3 [0.000]	752.9 [0.00]
Observation	3694	3694	3694	1580	3694	3694

Table 3.2c : Descriptive statistics of return series.

	SENSEX	SP_500	AFRICA_40	SP_ASIA	SP_EURO
Mean	0.053008	0.014093	0.014901	0.020811	-0.001188
Median	0.027992	0.030734	0.054953	0.038610	0.016502
Maximum	15.98998	10.95720	7.070682	13.30311	10.12568
Minimum	-11.80918	-9.469514	-7.736311	-8.585817	-8.152742
Std. Dev.	1.446564	1.228697	1.409361	1.349647	1.400656
Skewness	-0.083495	-0.216810	-0.378024	-0.063350	-0.024190
Kurtosis	12.30968	12.62812	5.689902	9.403630	7.675872
Jarque-Bera	13344.28	14297.12	939.7892	6314.051	3365.560
ARCH 1-2	30.03 [0.00]	213.5 [0.00]	49.56 [0.00]	139.7 [0.00]	95.26 [0.00]
ARCH 1-5	33.24 [0.00]	132.2 [0.00]	51.56 [0.00]	117.0 [0.00]	84.74 [0.00]
ARCH 1-10	28.95 [0.00]	81.7 [0.00]	33.98 [0.00]	74.92 [0.00]	46.35 [0.00]
Q(20)	54.05 [0.00]	82.1 [0.00]	57.79 [0.00]	44.42 [0.00]	44.12 [0.00]
Q^2(20)	835.7 [0.00]	3170.5 [0.00]	1224.3 [0.00]	2328.8 [0.00]	1604.9 [0.00]
Observations	3694	3694	2889	3694	3694

3.4 Methodology

In this study, recently developed Granger causality test in moments (Chen, 2016) has been used to examine the risk spillovers between developed and emerging stock markets. The test technique gives much more comprehensive information about the interactions between the markets because it allows to test the causality for the desired moments and takes into account the whole distribution. More precisely, unlike the existing Granger causality tests, this new test provides a test of Granger causality for both mean and variance as well as for all quantiles and moments.

Since the existing causality in variance tests (Cheung and Ng, 1996; Hong, 2001; Hafner and Herwartz, 2004, 2006, 2008; Dijk et al, 2005) allow us to test for Granger causality in the conditional variances of the series, they are very useful in the sense of comprehending mechanism of financial contagion and have been widely used in empirical studies. However, these tests do not provide information on tail dependency. In other words, they are away from testing the flight to quality or flight from quality because they are not designed for testing causality in the tail. The Granger causality test which was developed by Hong et al. (2009), allows to test causality only in a particular quantile while Chen's Granger causality test allows to test causality in mean, variance or in any quantile. Thus, while a single test can be used to test for financial contagion and flight to quality, it paves the way for a robust test with ideal properties that do not lead to statistical inaccuracies.

The assumptions that error terms have independent and identical distributions and that error terms of more than one model are mutually independent are not necessary in this test. Using this test, Granger causality can be tested for any moment (skewness, kurtosis, etc.) or for any quantile as well as Granger causality in mean and variance. This test can be applied to all of the residuals obtained from any econometric technique. Therefore it has a great flexibility of usage. Thus, tail dependency and risk causality (contagion and flight) can be tested statistically in a robust manner. The causality test in moments is a general test, combining and generalizing earlier Box-Pierce type Granger causality tests.

In this study, the AR (m) - GARCH model is estimated for bond returns and exponential GARCH model AR (m) - EGARCH (p, q) is estimated for stock returns considering volatility asymmetry. Following Chen (2016), Granger causality tests are performed between the two markets in mean and in variance as well as for combinations of (0, 0.2), (0.2, 0.4), (0.4, 0.6), (0.6, 0.8) and (0.8, 1) quantile pairs.

3.4.1 Test approach

Let $\{y_{it}\}$ be a sequence of stationary continuous random variables. Here, t represents time, and $Y_{i,t-1}$ represents the information set generated from $y_{i,t-k}$ for i = 1, 2 and for all $k>0$. Indicate $Y_{t-1}:=(Y_{1,t-1},Y_{2,t-1})$. Also assume $F_i(.|Y_{i,t-1})$ and $F_i(.|Y_{t-1})$ are respectively conditional distributions of $y_{it}|Y_{i,t-1}$ and $y_{it}|Y_{t-1}$ for i = 1, 2.

If $Y_{2,t-1}$ does not provide any contribution to the forecasting of $F_1(.|Y_{t-1})$ in such a way that

$$F_1(.|Y_{t-1}) = F_1(.|Y_{1,t-1}) \tag{3.2}$$

Then y_{2t} does not Granger cause of y_{1t} in distribution, otherwise y_{2t} Granger causes y_{1t} in distribution (Granger, 1980).

Let $\theta(.)$ be a p dimensional integral moment function. Equation 3.2 demonstrates that $Y_{2,t-1}$ is redundant for predicting $E\left[\theta(y_{1t})|Y_{t-1}\right]$, so y_{2t} is not Granger cause y_{1t} in moments:

$$E\left[\theta(y_{1t})|Y_{t-1}\right] = E\left[\theta(y_{1t})|Y_{1,t-1}\right] \tag{3.3}$$

3.4.2 Moment functions

Let T be the sample size for $\{y_{1t}, y_{2t}\}$. For a given moment function $\theta(.)$ and the univariate model $E\left[\theta(y_{it})\middle|Y_{i,t-1}\right]$, $\hat{\rho}_k$ be the sample correlation coefficient for the kth lag obtained from the transformed or untransformed residuals of the model $E\left[\theta(y_{1t})\middle|Y_{1,t-1}\right]$ and residuals of the model $E\left[\theta(y_{2t})\middle|Y_{2,t-1}\right]$. For example, u_{1t} and u_{2t} are obtained from two separate models. In this case, $\hat{\rho}_k$ is the sample correlation coefficient between u_{1t} and u_{2t-k}.

Moment function $\theta(.)$ may include followings but it is not limited to;

$\theta_1(y) := y$

$\theta_2(y) := y^2$

And

$\theta_q(\mathrm{y}) := \mathrm{I}\ (\mathrm{Q}_{it}(\tau_1) < \mathrm{y} \leq (\mathrm{Q}_{it}(\tau_2)\ ),$

$y \in \mathbb{R}$, $\tau_1 < \tau_2$, $\mathrm{I(A)}$, If the A event is true, the indicator function will take the value of 1 otherwise it will take that of 0. $\mathrm{Q}_{it}(\tau)$ indicates τ - quantile of $F_i(.|Y_{i,t-1})$ and $\tau \in [0,1]$. Moment functions can be related to the conditional mean, variance, and quantiles as follows:

Conditional mean:

$E\left[\theta(y_{1t})\middle|Y_{t-1}\right] = E\left[\theta(y_{1t})\middle|Y_{1,t-1}\right],$

Conditional variance:

$E\left[\theta_2\left(y_{1t} - E\left[\theta_1(y_{1t})\middle|Y_{1,t-1}\right]\right)\middle|Y_{1,t-1}\right] = \mathrm{var}\left[y_{1t}\middle|Y_{1,t-1}\right]$

and the conditional quantile:

$E\left[\theta_q(\mathrm{y}_{1t})\middle|Y_{1,t-1}\right] = \mathrm{E}\left[\mathrm{I}\ (\mathrm{Q}_{1t}(\tau_1) < \mathrm{y}_1 \leq (\mathrm{Q}_{1t}(\tau_2)\ )\middle|Y_{1,t-1}\right],$

The above three statements correspond to the test of the null hypothesis that y_{2t} does not Granger cause y_{1t} in mean, variance, and quantile respectively. In particular, when y_{1t} is a portfolio return and $(\tau_1, \tau_2) = (0, \tau)$ for small τ , $E\left[\theta_q(\mathrm{y}_{1t})\middle|Y_{1,t-1}\right]$ is a measure of Value at Risk (VaR). In this case by applying generalized test to $\theta(.) = \theta_q(.)$, we test whether y_{2t} does Granger cause y_{1t} in VaR. By considering $\theta(.)$ we examine whether y_{2t} does Granger cause y_{1t} in these moments.

3.4.3 Models

GARCH class of models are used for the financial data analysis such as:

$$y_{it} = \mu_{it}(\alpha_i) + \varepsilon_{it} h_{it}(\alpha_i)^{1/2} \tag{3.4}$$

here $\mu_{it}(\alpha_i)$ specifies $E\left[\mathrm{y}_{it} \middle| Y_{i,t-1}\right]$, $h_{it}(\alpha_i)$ refers to variance of $\left[\mathrm{y}_{it} \middle| Y_{i,t-1}\right]$, α_i indicates parameter vector which is estimated by the Gaussian quasi maximum likelihood (QML) method, and ε_{it} represents a standardized error so $E[\varepsilon_{it}] = 0$ and $E\left[\varepsilon_{it}^2\right] = 1$.

Let $m_{it}(\varphi_i)$ be a conditional moment model for $\mathrm{y}_{it}|Y_{i,t-1}$, with parameter vector φ_i and the parameter space Φ_i, or a conditional distribution model for $F_i\left(.\middle|Y_{i,t-1}\right)$, with the conditional probability density function (PDF): $f_{it}\left(.\middle|\varphi_i\right)$. More particularly, $m_{1t}(\varphi_1)$ is regarded as a conditional moment model for $E\left[\theta(\mathrm{y}_{1t})\middle|Y_{1,t-1}\right]$.

A conditional distribution model for $\mathrm{y}_{it}|Y_{i,t-1}$ may be constituted by adding a conditional probability density function for $\varepsilon_{it}|Y_{i,t-1}$, represented by $g_{it}\left(.\middle|\beta_i\right)$ with the parameter vector β_i to $y_{it} = \mu_{it}(\alpha_i) + \varepsilon_{it} h_{it}(\alpha_i)^{1/2}$.

Then, $f_{it}\left(.\middle|\varphi_i\right)$ takes the following form:

$$f_{it}\left(y\middle|\varphi_i\right) = \frac{1}{h_{it}(\alpha_i)^{1/2}} g_{it}\left(\frac{y-\mu_{it}(\alpha_i)}{h_{it}(\alpha_i)^{1/2}}\middle|\beta_i\right), \forall y \in \Re. \tag{3.5}$$

Conditional probability density function for $\varepsilon_{it}|Y_{i,t-1}$, $g_{it}\left(.\middle|\beta_i\right)$ is related by Hansen's (1994) skewed student's t density and Komunjer's (2007) asymmetric exponential power distribution (AEPD). This approach involves the conditional mean and variance for $\mathrm{y}_{it}|Y_{i,t-1}$:

$$m_{it}(\varphi_i) = \left(\mu_{it}(\alpha_i), h_{it}(\alpha_i)\right), \text{ with } \varphi_i = \alpha_i, \tag{3.6}$$

and the conditional distribution model for $\mathrm{y}_{it}|Y_{i,t-1}$:

$$m_{it}(\varphi_i) = f_{it}(.|\varphi_i), \text{ with } \varphi_i = \left(\alpha_i^T, \beta_i^T\right)^T. \tag{3.7}$$

I specify the equation (3.3) as an AR(1)-GARCH(1,1) model and equation (3.4) as an AR(1)-GARCH(1,1)-APD model to estimate and test $m_{it}(\theta_i)$.

I estimate the parameters of equation (3.3) by the Gaussian Quasi Maximum Likelihood method (QML) and those of equation (3.4) by the ML method, and apply the numerical optimization by using the Constrained Maximum Likelihood Estimation for GAUSSTM (Aptech Systems, Inc., Chandler, AZ, USA).

For the bond return, I specify equation (3.3) as the AR(1)-GARCH(1,1) model and equation (3.4) as the AR(1)-GARCH(1,1)-APD model. For the stock return I change the GARCH specification with the exponential GARCH (EGARCH) specification to take into account volatility asymmetry.

3.4.4 Cross correlation test

Let's define the following transformations of the error term corresponding to the moment functions $\theta_1(.), \theta_2(.), \theta_q(.)$.

$$\Theta_{it}^{(1)} := \varepsilon_{it},$$
$$\Theta_{it}^{(2)} := \varepsilon_{it}^2 - 1$$

And

$$\Theta_{it}^{(q)} := \mathrm{I}\,(\mathrm{Q}_{\varepsilon,it}(\tau_1|\beta_i) < \varepsilon_{it} \leq (\mathrm{Q}_{\varepsilon,it}(\tau_2|\beta_i))) - (\tau_2 - \tau_1),$$

Here $\mathrm{Q}_{\varepsilon,it}(\tau|\beta_i)$ indicates to τ -quantile of $g_{it}(.|\beta_i)$.

$\Theta_{it} := \Theta_{it}(\varphi_i)$, $\Theta_{it}{}^{(1)}, \Theta_{it}{}^{(2)}, \Theta_{it}{}^{(q)}$ is a transformation of ε_{it} for i=1,2. Functional form of Θ_{1t} and Θ_{2t} may be different.

$\Theta_{i,ot} := \Theta_{it}(\theta_{i0})$, $\Theta^c{}_{i,ot} := \Theta_{i,ot} - E\left[\Theta_{i,ot}\right]$, $\sigma_i{}^2 := E\left[\left(\Theta^c{}_{i,ot}\right)^2\right]$, $\hat{\Theta}_{it} := \Theta_{it}(\hat{\varphi}_{it})$, $\bar{\Theta}_i = P^{-1}\sum_{t=R+1}^{T}\hat{\Theta}_{it}$, $\hat{\Theta}_{it}^c := \hat{\Theta}_{it} - \bar{\Theta}_i$ and $\bar{\sigma}_i{}^2 := P^{-1}\sum_{t=R+1}^{T}(\hat{\Theta}_{it}^c)^2$

We can use generalized cross-correlations to determine how is the relationship between current shock $\Theta_{1,ot}$ of a variable and $\Theta_{2,ot-k}$ k-lag shock of another variable:

$$\rho_k := corr(\Theta_{1,ot}, \Theta_{2,ot-k}) = \frac{1}{\sigma_1\sigma_2} E\left[\Theta^c{}_{1,ot}, \Theta^c{}_{2,ot-k}\right], \tag{3.8}$$

$k = 1, \ldots, n,\ n \ll P$

Corresponding to the above cross-correlation of the sample can be expressed as:

$$\hat{\rho}_k := \frac{1}{P-k} \sum_{t=R+1+k}^{T} \left(\frac{\hat{\Theta}^c_{1t}}{\bar{\sigma}_1}\right)\left(\frac{\hat{\Theta}^c_{2,t-k}}{\bar{\sigma}_2}\right) \tag{3.9}$$

$\hat{\rho} := (\hat{\rho}_1, \hat{\rho}_2, ..., \hat{\rho}_n)'$ ve $\hat{V} := (\bar{\sigma}_1\bar{\sigma}_2) \times I_n$

Chen (2016) showed that under the weak assumptions, the following statement is valid for $x_t = diag(\Theta^c{}_{2,t-k})$ and $\xi_t = \Theta_{1t} \times \iota_n$.

$$\hat{V}\sqrt{P\hat{\rho}} = \frac{1}{\sqrt{P}} \sum_{t+R+1}^{T} \hat{x}_t \hat{\xi}_t + o_p(1) \tag{3.10}$$

Here $\iota_n := (1,....,1)'$ symbolize the $n \times 1$ vector of ones and $diag(\Theta^c{}_{2,t-k})$ denotes diagonal matrix with k[th] diagonal element $\Theta^c{}_{2,t-k}$ for k=1,....,n .

S is the qxn weight matrix for $q \le n$, $\hat{\Omega}$ is the variance covariance matrix. In this case, the generalized cross-correlation test statistics is:

$$G_\rho := P(S\hat{\rho})'(S\hat{V}^{-1}\hat{\Omega}\hat{V}^{-1}S')(S\hat{\rho}) \tag{3.11}$$

With the asymptotic distribution: $G_\rho \xrightarrow{d} \chi^2(q)$ under the hypothesis of

$E\left[\theta(y_{1t})\middle| Y_{t-1}\right] = E\left[\theta(y_{1t})\middle| Y_{1,t-1}\right]$.

G_ρ test is one of the cross correlation tests for Granger causality in moments. This test can be applied to different pairs of $(\Theta_{1t}, \Theta_{2t})$ in order to test Granger causality in mean $\Theta_{1t} = \Theta^{(1)}{}_{1t}$, to test for Granger causality in variance $\Theta_{1t} = \Theta^{(2)}{}_{1t}$, and to test Granger causality in quantile $\Theta_{1t} = \Theta^{(q)}{}_{1t}$.

3.5 Empirical Findings

In this part, the *Gρ* test is applied which was advanced by Chen (2016) to create a class of cross-correlation tests for Granger causality in mean, variance and quantile. In this class of tests structure, $\{y_{1t}, y_{2t}\}$ is a pair of financial return sequences. Hence, we can apply the *Gρ* test for checking whether y_{2t} Granger-causes y_{1t} in mean, variance and quantile.

The $G\rho$ test represents a class of cross-correlation tests for Granger causality in moments. It is fitting to various (Θ_{1t}, Θ_{2t})'s, incorporating $\Theta_{1t} = \Theta_{1t}^{(1)}$ for testing Granger causality in mean, $\Theta_{1t} = \Theta_{1t}^{(2)}$ for testing Granger causality in variance and $\Theta_{1t} = \Theta_{1t}^{(q)}$ for testing Granger causality in quantile q.

Aforesaid, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(1)}, \Theta_{2t}^{(1)})$ and $(\Theta_{1t}^{(2)}, \Theta_{2t}^{(2)})$ we examine whether and how $\{y_{2t}\}$ Granger causes $\{y_{1t}\}$ in mean and in variance respectively. These two settings are respectively practical for assessing the predictability of y_{1t} contributed by the lagged return shocks of y_{2t} and for appraising the volatility spillover from one to the other market. Moreover, this test can be used to check for Granger-causality in other moments, like the tails. Therefore, for the two time series $\{y_{1t}\}$ and $\{y_{2t}\}$, the test checks whether an extreme downside risk from $\{y_{2t}\}$ has a predictive content for an extreme downside risk for $\{y_{1t}\}$.

3.5.1 Granger causality tests in moments between BIST 100 and regional markets

In first analysis, let $P_t^{BIST100}$ and P_t^{SPEU} are respectively the Turkish stock market index (BIST 100) and the Standard and Poor's Europe Stock Market Index (SPEU) on the t^{th} trading date. Let's denote the Turkish stock market index return as: $y_t^{BIST100} = 100 \times (\ln(P_t^{BIST100}) - \ln(P_{t-1}^{BIST100}))$ and the SPEU return as $y_t^{SPEU} = 100 \times (\ln(P_t^{SPEU}) - \ln(P_{t-1}^{SPEU}))$. Then, $(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{SPEU})$ was set, in order to investigate whether and how Standard and Poor's Europe Stock Market Index return Granger-causes the Turkish stock market index return and $(y_{1t}, y_{2t}) = (y_t^{SPEU}, y_t^{BIST100})$ for exploring whether and how the Turkish stock market index return Granger causes the Standard and Poor's Europe Stock Market Index return.

In ongoing analysis, (y_{1t}, y_{2t}) was set as a pair of other financial stock returns from our sample countries and we proceed with the same test structure in order to test for contagion effect.

In Table 3.3, the $G\rho$ test statistics with $S = I_n$ and n = 1, 5, 10 are presented. Main findings are summarized as follows.

Firstly, one may observe that the Standard and Poor's Europe Stock Market Index (SPEU) could Granger-cause the Turkish stock market index (BIST 100) in mean.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{SPEU})$ with $n = 1$ but insignificant for all the other cases being considered suggesting that the left tail of the Standard and Poor's Europe Stock Market Index

(SPEU) distribution, could weakly Granger cause the left tails of the Turkish stock market index (BIST 100). These results indicate that there exists contagion in negative periods and in general European market can regarded as the driver of spillover.

Table 3.3 : G test Statistics for BIST 100 and SPEU.

Granger causality in moments

			$(y_{1t}, y_{2t}) = (y_t^{BIST}, y_t^{SPEU})$							$(y_{1t}, y_{2t}) = (y_t^{SPEU}, y_t^{BIST})$						
Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
$\Theta_{2t}^{(1)}$	1		**17.08*** **	0.01	14.4***	3.479	0.109	2.912	13.4***	1.606	2.692	10.2***	0.25	6.5***	0.588	0.257
	5		**19.9*** **	4.730	18.5***	8.993	9.694	13.8***	16.4***	9.337	14.04***	15.1***	1.748	12.3**	3.671	7.747
	10		**22.9*** **	9.362	23.1***	14.705	17.7**	22.6***	17.644	11.366	19.07**	19.9**	6.014	13.247	6.951	13.203
$\Theta_{2t}^{(2)}$	1		0.873	0.375	0.023	2.124	1.011	0.007	0.875	1.883	1.947	0.161	1.466	1.088	1.963	4.647
	5		5.169	8.428	3.147	3.420	3.648	1.097	3.051	3.246	5.600	3.291	3.102	15.2***	5.392	5.333
	10		13.912	13.216	9.547	3.868	5.545	4.053	6.444	6.625	11.518	6.285	7.662	21.7***	12.947	11.222
$\Theta_{2t}^{(q1)}$	1		16.1***	0.013	**7.4*** **	2.221	0.308	1.815	13.2***	0.284	0.008	1.745	0.529	3.517	0.157	0.005
	5		17.5***	2.566	8.099	5.641	7.275	11.5**	17.06***	4.735	7.119	2.321	1.774	8.134	1.922	5.498
	10		22.2***	7.458	9.643	15.237	15.680	15.831	21.6***	10.674	9.307	11.318	4.709	9.436	8.028	13.194
$\Theta_{2t}^{(q2)}$	1		0.014	1.670	1.692	0.02	5.2**	0.067	0.96	1.145	4.5**	4.7**	0.02	1.763	5.141	1.164
	5		6.129	4.214	5.862	14.7***	10.429	1.147	8.820	8.555	10.6**	9.520	4.889	6.453	7.312	4.163
	10		8.591	8.214	7.528	18.6**	13.426	3.950	12.800	11.992	15.749	13.079	17.433	10.881	8.547	7.603
$\Theta_{2t}^{(q3)}$	1		2.575	6.1***	1.874	0.582	1.394	1.577	0.049	0.092	0.011	0.402	2.251	0.277	2.572	0.097
	5		7.362	14.8***	5.053	0.983	12.01**	5.922	3.216	9.085	3.169	7.246	2.453	4.954	4.725	10.188
	10		10.533	19.9**	15.182	12.368	15.761	7.095	7.375	15.297	4.676	11.232	6.261	21.633	12.214	18.802
$\Theta_{2t}^{(q4)}$	1		0.913	4.1**	0.796	1.914	3.048	0.405	0.814	0	0	0.05	1.200	0.154	0.397	0.066
	5		2.313	6.598	2.168	4.746	8.289	2.723	2.559	2.106	3.370	3.433	4.156	8.184	1.550	3.372
	10		2.888	8.001	4.267	10.727	13.590	5.260	4.934	4.414	7.624	6.801	13.852	11.216	5.502	5.959
$\Theta_{2t}^{(q5)}$	1		3.437	1.338	4.3**	0.326	1.795	0.794	3.158	1.576	4.7**	14.8***	2.460	8.2***	0.055	0.955
	5		5.957	12.6**	7.686	2.613	12.2**	10.343	7.324	9.460	11.02**	20.1***	5.206	9.301	1.650	7.998
	10		8.757	20.03**	15.823	10.066	17.133	15.889	8.041	15.760	13.843	25.06***	10.889	15.681	4.129	20.254

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

The second index pair is the Turkish stock market index (BIST 100) and S&P Africa 40 index. By setting $(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{AFR})$, whether and how S&P Africa 40 Index return Granger causes the Turkish stock market index return was investigated. And again by setting $(y_{1t}, y_{2t}) = (y_t^{AFR}, y_t^{BIST100})$, whether and how the Turkish stock market index return Granger causes the S&P Africa 40 Index return was examined. From the Table 3.4 we might conclude that the S&P Africa 40 return could Granger-cause the Turkish stock market return (BIST 100) in mean but not in variance.

Given $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t})= (y_t^{BIST100}, y_t^{AFR})$, suggesting that the left tail of the S&P Africa 40 index could Granger cause the left tail of the Turkish stock market index (BIST 100). On the other hand by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t})= (y_t^{AFR}, y_t^{BIST100})$, suggesting that the left tail of Turkish stock market index (BIST 100) could Granger cause the left tail of the S&P Africa 40 index. These results indicates that there exists bilateral financial contagion in the falling market periods.

Contagion effect between Turkey and Africa stock markets may result from the trade relations. Turkey has been a strategic partner of the Continent by the African Union since January 2008. And also, Turkey have signed Trade and Economic Cooperation Agreements with 38 African countries.

Table 3.4 : G test Statistics for BIST 100 and S&P Africa 40.

			$(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{AFR})$							$(y_{1t}, y_{2t}) = (y_t^{AFR}, y_t^{BIST100})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1	**22.9*** **	1.254	14.7***	3.6**	5.8***	0.817	**6.6*** **	1.614	0.748	4.782	3.6**	0.075	0.158	11.1***
		5	**24.6*** **	4.985	20.9***	5.186	7.349	10.3**	**9.7***	11.1**	6.912	6.923	5.126	11.0**	2.546	15.08***
		10	**26.04*** **	16.368	28.5***	8.018	15.162	25.1***	**13.635**	17.8**	27.07***	10.937	6.003	19.4**	10.923	36.1***
	$\Theta_{2t}^{(2)}$	1	0.226	1.689	0.278	0.005	1.866	0.013	0.121	1.013	1.253	1.307	2.669	0.074	4.1**	2.8*
		5	1.114	6.799	6.684	8.891	15.2***	12.06**	4.563	3.734	10.4*	3.528	11.4**	7.904	11.5**	6.080
		10	6.967	8.893	9.555	17.620	16.6*	20.8**	5.827	6.186	19.3**	11.452	23.4***	10.009	16.8*	13.064
	$\Theta_{2t}^{(q1)}$	1	13.3***	3.182	**8.9*** **	6.04***	17.7***	0	3.507	2.465	1.982	**6.1*** **	0.504	0.525	1.134	2.8*
		5	21.5***	4.572	**18.1*** **	6.956	18.4***	4.801	4.810	4.351	4.371	**9.2***	3.071	7.825	4.079	4.308
		10	24.8***	13.757	**20.01** **	9.158	20.8**	13.014	7.729	21.4***	9.304	**17.8** **	3.634	13.709	6.371	26.5***
	$\Theta_{2t}^{(q2)}$	1	4.6**	1.595	7.7***	4.1**	0.032	1.118	0.157	2.458	3.981	0.19	0.509	0.551	0.061	4.4**
		5	11.9**	5.466	17.9***	7.699	1.968	5.746	4.651	11.8**	5.556	6.090	16.7***	5.471	2.887	11.3**
		10	13.639	10.796	20.1**	11.181	3.468	11.568	6.135	15.860	8.219	10.170	19.6**	10.893	8.757	12.731
	$\Theta_{2t}^{(q3)}$	1	1.406	2.172	2.681	0.002	2.910	0.035	0.013	1.066	0.346	0.969	2.014	3.536	0.232	0.468
		5	2.310	5.519	3.314	5.775	5.595	12.034	1.968	2.800	1.059	1.971	16.5***	4.463	10.053	4.368
		10	3.480	14.396	6.238	8.387	11.927	15.162	3.474	3.353	3.322	4.417	18.3**	6.450	13.091	6.131
	$\Theta_{2t}^{(q4)}$	1	1.846	1.717	1.424	0.156	0.978	0.009	0.377	0.002	2.251	0.391	1.141	0.589	1.444	0.054
		5	3.288	8.396	4.921	4.414	5.273	10.785	5.149	1.696	12.343	3.904	3.281	4.861	4.474	3.714
		10	5.020	24.816	8.702	17.956	15.006	15.235	13.580	3.457	14.719	5.381	7.303	9.168	11.294	10.363
	$\Theta_{2t}^{(q5)}$	1	14.3***	1.093	**13.0*** **	0.069	1.127	1.433	2.064	3.520	0.298	2.308	3.2*	0.891	0.49	7.8***
		5	15.9***	7.809	**18.3*** **	2.489	3.330	8.643	3.871	7.703	15.1***	3.759	10.6**	16.4***	2.430	15.03***
		10	16.9*	23.815	**28.4*** **	7.129	8.150	19.664	9.815	12.794	21.3***	5.434	12.838	18.3**	15.197	29.0***

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

The third index pair is the Turkish stock market index (BIST 100) and the Standard and Poor's Asia Stock Market Index (SPAS50). By setting (y_{1t} , y_{2t}) = ($y_t^{BIST100}$, y_t^{SPAS50}), whether and how the Standard and Poor's Asia Stock Market Index (SPAS50) return Granger causes the Turkish stock market index return was investigated. And again by setting (y_{1t} , y_{2t}) = (y_t^{SPAS50}, $y_t^{BIST100}$), whether and how the Turkish stock market index return Granger causes the Standard and Poor's Asia Stock Market Index (SPAS50) return was examined. From the analysis of third index pair in Table 3.5 we may conclude that the Standard and Poor's Asia Stock Market Index (SPAS50) return could weakly Granger-cause the Turkish stock market index (BIST 100) in mean and Granger-cause in variance, and also in left tail of the distribution. In addition, we can see from the table that the Turkish stock market index (BIST 100) return could Granger-cause the Standard and Poor's Asia Stock Market Index (SPAS50) almost everywhere of the distribution.

In this regard, our findings imply that there is a strong interdependence between Turkish stock market index (BIST 100) and Standard and Poor's Asia Stock Market Index (SPAS50).

Table 3.5 : G test Statistics for BIST 100 and SPAS50.

			$(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{SPAS50})$								$(y_{1t}, y_{2t}) = (y_t^{SPAS50}, y_t^{BIST100})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		4.5**	0.386	3.8**	2.237	0.225	0.061	0	79.6***	1.264	52.2***	10.08***	0.441	8.5***	49.3***
		5		6.604	9.6**	18.09***	3.998	3.465	12.6**	2.051	83.3***	4.495	60.9***	17.5***	1.935	18.2***	53.1***
		10		15.438	21.7***	21.9***	6.889	9.394	18.3**	14.105	89.9***	19.804	68.0***	28.6***	3.615	20.3**	60.4***
	$\Theta_{2t}^{(2)}$	1		3.302	3.9**	0.375	0.133	5.08**	0.091	3.492	0.962	6.8***	4.2**	3.4*	1.785	0	0.392
		5		5.115	15.6***	3.235	4.232	8.884	1.950	6.481	5.564	9.6*	8.204	10.9**	18.3***	8.640	7.015
		10		15.202	25.2***	10.960	9.152	22.7***	5.243	13.146	8.041	14.223	8.777	18.7**	23.3***	13.262	9.083
	$\Theta_{2t}^{(q1)}$	1		0.933	3.9**	8.2***	5.059	8.8***	0.423	0.825	58.09***	5.9***	39.6***	3.07*	0.032	15.1***	28.4***
		5		9.4*	10.2**	24.6***	6.106	11.5**	7.596	5.100	62.6***	8.272	47.3***	9.8*	1.364	24.5***	30.2***
		10		17.07*	18.1**	30.7***	9.015	16.7*	11.859	15.064	73.7***	19.6**	61.0***	12.887	6.350	26.05***	34.5***
	$\Theta_{2t}^{(q2)}$	1		1.719	0.428	0.216	1.784	0.776	0.372	1.102	13.9***	0.24	3.3*	11.6***	6.4***	0.268	7.535
		5		18.3***	3.424	10	3.540	2.879	6.298	14.6***	23.5***	2.412	7.648	14.4***	14.8***	0.63	21.428
		10		22.9***	7.923	14.787	4.758	8.073	14.988	20.2**	26.3***	5.698	8.915	16.2***	21.1**	5.761	29.637
	$\Theta_{2t}^{(q3)}$	1		0.091	9.6***	1.041	0.095	4.03**	0.103	0.13	3.6**	0.018	1.727	2.078	4.4**	0.016	0.381
		5		2.764	12.5**	5.197	1.005	13.03**	3.625	4.517	11.8**	10.2**	2.481	7.264	11.4**	10.411	9.467
		10		3.705	21.5***	7.526	2.058	15.513	4.735	5.570	15.794	17.6**	7.831	16.844	19.2**	13.424	14.835
	$\Theta_{2t}^{(q4)}$	1		3.492	14.6***	0.068	0.699	1.968	0.108	7.07***	3.9**	5.1**	2.250	0.401	0.608	3.6**	0.765
		5		13.4***	18.5***	0.805	2.109	6.252	0.775	15.5***	9.6*	27.6***	13.6***	8.237	1.043	14.3***	3.235
		10		17.4**	23.6***	8.328	7.985	11.912	4.550	18.3**	13.023	30.09***	16.4*	13.696	8.871	19.4**	12.162
	$\Theta_{2t}^{(q5)}$	1		14.5***	1.807	3.414	0.097	1.978	0.006	6.9***	58.5***	0.463	42.04***	10.9***	0.847	5.3**	28.4***
		5		18.5***	8.757	7.211	0.516	10.7**	9.824	11.2**	59.3***	3.831	45.3***	15.9***	2.915	8.060	30.1***
		10		26.1***	26.5***	13.029	2.245	19.8**	18.3**	22.5***	65.5***	17.209	47.3***	27.3***	3.711	9.946	41.6***

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.6, there exist a weak contagion between SPEU and BIST 100; a bilateral contagion between S&P Africa 40 and BIST 100; and strong interdependence between SPAS 50 and BIST 100.

Table 3.6 : Summary of Test Results between BIST 100 and Regional Markets.

	Direction of causality	
Negative Contagion		SPEU→BIST 100 (weakly)
Negative Contagion	BIST 100→S&P Africa40	S&P Africa 40→BIST 100
Interdependence	BIST 100→SPAS 50	SPAS 50→BIST 100

3.5.2 Granger causality tests in moments between BIST 100 and developed markets

As can be seen from Table 3.7 there is a causal relationship between U.S. stock market index (S&P 500) and Turkish stock market index (BIST 100). We can observe from the significance of the test statistics that the U.S. stock market index (S&P 500) may Granger-cause the Turkish stock market index (BIST 100) in mean but not in variance.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for (y_{1t}, y_{2t})= $(y_t^{BIST}, y_t^{SP500})$, suggesting that the left tail of the U.S. stock market index (S&P 500) distribution, could Granger cause the left tails of Turkish stock market index (BIST 100). These results indicates that there exist contagion in falling stock market periods and it seems that U.S. stock market index (S&P 500) is the driver of spillover.

Table 3.7 : G test Statistics for BIST 100 and S&P 500.

				$(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{SP500})$							$(y_{1t}, y_{2t}) = (y_t^{SP500}, y_t^{BIST100})$						
	Θ_{2t}	n	Θ_{1t}=	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**107.2*****	0.049	79.8***	13.05***	0.129	11.7***	88.04***	0.03	4.1**	0.736	0.045	0.016	3.290	1.862
		5		**114.8*****	3.110	84.3***	16.2***	3.883	22.9***	90.03***	5.164	15.9***	6.186	4.263	7.538	7.493	15.6***
		10		**120.5*****	9.587	87.9***	19.4**	12.702	28.7***	100.9***	8.025	22.2***	8.966	8.855	11.974	14.147	17.191
	$\Theta_{2t}^{(2)}$	1		10.8***	0.491	3.6**	0.64	0.082	0.333	6.7***	0.769	0.107	0.003	0.328	2.537	1.958	1.470
		5		17.8***	4.420	8.832	2.512	6.225	3.808	9.725	2.147	5.382	4.419	3.154	18.1***	4.453	2.892
		10		25.2***	8.374	14.183	6.789	16.846	7.569	19.9**	5.650	19.102	10.607	7.766	31.9***	5.023	5.227
	$\Theta_{2t}^{(q1)}$	1		60.6***	0.002	**37.3*****	3.404	0.194	7.9***	50.04***	0.009	1.321	0.015	0.242	0	0.032	0.169
		5		65.6***	1.356	**40.9*****	9.870	2.643	19.2***	51.4***	7.064	12.2**	4.055	2.738	5.360	3.354	13.8***
		10		68.6***	7.917	**46.8*****	10.839	12.861	20.4**	58.5***	15.399	23.9***	13.988	10.053	6.930	9.964	17.097
	$\Theta_{2t}^{(q2)}$	1		6.5***	0.004	4.8**	2.587	4.847	0.441	6.01***	0.238	3.444	4.105	1.146	8.886	3.863	2.336
		5		8.727	0.868	7.597	4.604	6.558	4.892	10.430	3.142	11.6**	5.666	3.411	11.015	8.218	6.462
		10		17	5.390	15.291	14.978	10.072	8.341	14.363	6.796	16.172	9.531	8.063	12.923	16.357	12.567
	$\Theta_{2t}^{(q3)}$	1		4.3**	1.082	0.363	0.405	0.024	0.775	2.723	0.109	0.803	0.087	0.201	0.064	0.446	0.118
		5		5.726	5.299	2.897	1.897	5.742	1.924	3.874	0.799	5.073	1.436	4.800	3.160	13.5***	1.299
		10		11.765	11.231	11.187	3.190	8.011	3.506	8.684	9.477	20.1**	8.038	7.722	9.067	16.354	7.964
	$\Theta_{2t}^{(q4)}$	1		2.066	0.861	3.995	0.193	0.936	0.015	1.469	0.221	0.079	5.042	1.599	8.2***	0.012	0.048
		5		11.2**	7.473	16.3***	5.771	6.089	1.367	6.720	1.746	9.098	8.966	3.147	11.7**	1.916	3.465
		10		17.293	11.254	20.6**	13.195	8.397	5.640	10.712	5.023	23.1***	21.002	6.377	14.964	8.509	5.333
	$\Theta_{2t}^{(q5)}$	1		42.6***	0.038	51.2***	6.1***	0.165	6.8***	25.2***	0.021	3.405	0.043	0.019	0.109	4.308	2.821
		5		57.5***	0.912	61.4***	9.157	3.380	17.7***	29.2***	5.124	11.8**	4.981	4.419	4.611	7.778	6.424
		10		60.1***	6.095	66.5***	18.7**	10.924	28.3***	30.4***	8.370	13.196	5.705	8.149	7.634	15.140	10.400

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

The other country pair is Turkish stock market index (BIST 100) and German stock market index (DAX 100). As can be seen from Table 3.8, we might conclude that the G test statistic is significant with *n* = 1 but insignificant for all the other cases being considered. The German stock market index (DAX 100) could weakly Granger-cause the Turkish stock market index (BIST 100) in mean but not in variance, and the Turkish stock market index (BIST 100) may Granger-cause the German stock market index (DAX 100) neither in mean nor in variance.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{DAX\ 100})$, with *n* = 1 but insignificant for all the other cases being considered, suggesting that the left tail of the German stock market index (DAX 100) distribution, could weakly Granger cause the left tails of the Turkish stock market index (BIST 100).

Table 3.8 : G test Statistics for BIST 100 and DAX 100.

				$(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{DAX\ 100})$							$(y_{1t}, y_{2t}) = (y_t^{DAX\ 100}, y_t^{BIST100})$						
	Θ_{2t}	n	Θ_{1t}=	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**8.2*****	0.003	7.3***	5.8***	0.993	6.05***	3.6**	3.420	3.6**	10.8***	0.013	1.142	5.8***	0.013
		5		8.942	6.030	10.315	10.3**	5.649	13.8***	5.914	9.351	17.7***	16.5***	3.610	4.840	9.134	7.526
		10		13.835	13.587	16.258	19.4**	15.631	25.1***	12.782	11.703	21.9***	24.06***	12.637	9.553	16.905	12.498
	$\Theta_{2t}^{(2)}$	1		3.422	0.517	0.211	2.770	0.709	0.351	3.057	0.266	1.509	4.07**	0.478	2.870	0.477	1.281
		5		5.159	4.312	1.510	3.521	1.601	3.284	5.688	3.481	12.3**	8.345	4.935	23.3***	4.416	10.422
		10		5.702	6.634	3.391	5.061	2.428	6.706	6.913	6.774	20.8**	11.617	11.169	27.1***	17.9**	16.002
	$\Theta_{2t}^{(q1)}$	1		6.2***	0.049	**5.04****	3.159	0.766	3.6**	2.651	0.518	0.415	2.727	0.003	0.366	1.432	0.009
		5		7.156	4.166	7.913	7.173	3.369	12.6**	4.668	7.594	7.352	5.656	1.690	5.433	5.185	9.646
		10		10.233	12.512	11.549	13.680	12.632	17.227	11.584	10.228	13.006	14.235	8.221	12.525	9.149	15.730
	$\Theta_{2t}^{(q2)}$	1		3.111	1.535	1.902	0.065	0.855	0.201	0.51	1.270	1.186	2.274	0.037	0.201	5.9***	0.52
		5		9.873	7.935	6.394	9.863	9.496	4.688	5.515	8.187	6.736	5.592	8.651	2.470	8.610	5.670
		10		15.381	12.176	9.052	14.007	15.933	6.303	14.809	9.540	19.9**	8.565	15.321	8.313	13.104	7.420
	$\Theta_{2t}^{(q3)}$	1		0.997	5.1**	0.004	0.354	0.636	1.433	0.47	1.037	0.113	0.579	0.614	1.822	0.207	0.632
		5		7.986	11.2**	6.568	1.393	7.593	4.277	2.107	9.047	2.903	5.958	4.048	4.611	2.563	10.424
		10		9.908	18.5**	9.779	8.308	10.190	10.590	2.897	13.522	5.670	10.950	8.765	8.179	5.511	12.529
	$\Theta_{2t}^{(q4)}$	1		9.6***	0.879	7.8***	0.068	0.002	0.283	4.3**	0	0.02	0.124	0.64	0.223	0.472	0.001
		5		15.2***	5.772	14.9***	10.394	3.439	6.419	12.8**	3.016	9.347	2.578	1.235	7.720	2.122	9.167
		10		19.8**	15.391	22.5***	12.767	11.202	11.268	20.3**	7.583	15.891	13.494	8.448	13.393	7.271	13.053
	$\Theta_{2t}^{(q5)}$	1		0.194	0.355	1.940	0.608	0.689	3.504	0.221	0.658	3.8**	4.4**	0.084	2.857	4.028	1.719
		5		3.294	9.452	5.328	5.123	10.6**	10.168	7.138	3.972	12.9**	7.488	6.484	4.636	6.499	6.690
		10		10.579	19.6**	17.328	19.3**	22.5***	15.640	14.495	11.001	15.444	16.120	13.287	8.034	13.339	13.744

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

From the analysis results in Table 3.9 we may conclude that UK stock market index (FTSE 100) could Granger-cause the Turkish stock market index (BIST 100) in mean but not in variance, the Turkish stock market index (BIST 100) may Granger-cause the UK stock market index (FTSE 100) neither in mean nor in variance. By setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q1)}$, $\Theta_{2t}^{(q1)}$), the G test statistic is significant for (y_{1t}, y_{2t}) = (y_t^{BIST}, $y_t^{FTSE\ 100}$) with n = 1,5 suggesting that the left tail of the UK stock market index (FTSE 100) distribution, could Granger cause the left tails of the Turkish stock market index (BIST 100). These results indicates that there exist contagion in falling stock market periods and it seems that FTSE 100 is the driver of spillover.

Table 3.9 : G test Statistics for BIST 100 and FTSE 100.

	Θ_{2t}	n	Θ_{1t}=	$(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{FTSE100})$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$(y_{1t}, y_{2t}) = (y_t^{FTSE100}, y_t^{BIST100})$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**19.5*** **	0.032	20.1***	3.511	0.538	4.7***	12.8***	0.292	1.010	1.193	0.053	0.004	2.613	0.08
		5		**24.5*** **	2.269	21.4***	5.931	9.457	17.03***	13.9***	4.568	16.09***	10.6**	5.275	8.686	5.528	10.660
		10		**29.1*** **	10.449	25.3***	12.154	16.946	30.6***	22.8***	8.836	24.9***	19.2**	8.727	14.374	7.928	14.733
	$\Theta_{2t}^{(2)}$	1		5.9***	1.851	0.026	1.570	0.321	1.264	1.543	1.267	0.006	0.015	2.154	0.363	0.475	0.388
		5		9.396	7.058	4.092	2.938	3.699	3.161	4.346	2.323	2.945	4.123	4.358	12.5***	6.878	5.050
		10		14.057	8.240	11.325	5.456	9.862	11.579	9.322	3.788	10.612	9.150	10.922	20.5**	15.952	7.039
	$\Theta_{2t}^{(q1)}$	1		13.2***	2.708	**10.3*** **	1.037	0.721	2.475	4.770	0.343	0.181	0.207	1.227	0.004	2.339	0.003
		5		15.4***	6.737	**12.1** **	6.921	4.753	11.7**	5.255	6.948	5.841	3.932	9.261	16.118	5.922	15.9***
		10		23.7***	8.429	15.706	15.837	12.369	21.8***	12.402	18.762	10.548	14.917	11.132	17.693	9.066	26.5***
	$\Theta_{2t}^{(q2)}$	1		0.007	0.749	0.821	0.203	2.145	0.35	0.068	0.054	2.982	0.004	0.182	1.251	0.435	0.002
		5		3.137	3.066	2.342	4.171	6.407	6.154	3.113	13.455	7.394	6.483	7.336	2.870	1.676	10.9**
		10		6.018	3.880	7.892	10.297	13.251	13.376	5.119	16.065	14.157	8.999	9.634	6.784	4.572	11.277
	$\Theta_{2t}^{(q3)}$	1		0.093	11.2***	0.067	0.531	3.433	0.864	1.819	0.066	0.851	0.672	1.080	0.393	1.826	0.622
		5		7.034	16.2***	3.950	3.718	5.087	8.043	8.734	10.431	2.715	9.462	3.037	9.145	17.03***	2.652
		10		11.278	26.8***	8.389	8.434	7.044	19.832	10.348	12.804	8.778	13.406	14.597	12.221	19.01**	4.301
	$\Theta_{2t}^{(q4)}$	1		3.100	10.4***	3.033	0	0.199	0.188	0.693	0.457	0.525	0.005	0.295	0.409	0.438	0.502
		5		11.2**	13.5***	9.069	6.818	5.248	3.221	2.102	2.328	8.393	2.290	3.411	7.222	0.967	4.451
		10		16.240	17.684	12.709	10.607	9.616	11.922	4.793	3.810	16.689	5.683	9.698	12.236	4.278	5.204
	$\Theta_{2t}^{(q5)}$	1		4.05**	2.254	6.1***	1.840	0.014	1.885	5.097	1.254	1.984	1.444	0.01	0.01	2.046	0.002
		5		5.219	6.406	9.377	3.498	4.627	13.8***	6.310	6.630	7.887	6.713	5.601	1.748	7.716	4.262
		10		10.418	15.503	21.3***	9.955	9.494	20.9**	10.021	13.744	13.828	13.016	8.101	6.500	10.541	14.025

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.10 we might conclude that the Turkish stock market index (BIST 100) could Granger-cause the Japan stock market index (NIKKEI 225) in mean, and weakly Granger cause in variance. On the other hand, Japan stock market index (NIKKEI 225) could Granger-cause the Turkish stock market index (BIST 100) neither in mean nor in variance.

By analyzing causal relationship between the tails of these distributions we may conclude that neither BIST 100 nor NIKKEI 225 Granger cause each other. These results indicate weak evidence of a link.

Table 3.10 : G test Statistics for BIST 100 and NIKKEI 225.

			$(y_{1t}, y_{2t}) = (y_t^{BIST100}, y_t^{NIKKEI\ 225})$								$(y_{1t}, y_{2t}) = (y_t^{NIKKEI\ 225}, y_t^{BIST100})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		0.617	0.221	0.573	1.644	0.051	0.128	0.127	**61.4*** **	0.046	70.370	3.137	2.741	1.190	58.743
		5		8.467	3.225	4.389	2.557	1.493	6.404	5.518	**65.6*** **	6.888	73.702	7.227	10.054	8.382	61.268
		10		9.958	21.546	9.154	4.972	15.632	8.613	13.390	**70.7*** **	15.295	73.929	10.406	12.509	13.363	69.127
	$\Theta_{2t}^{(2)}$	1		0.298	0.62	0.292	0.782	0.902	3.840	1.146	2.113	**5.7*** **	2.130	5.222	0.004	0.133	0.527
		5		1.777	3.572	2.487	1.933	12.500	8.560	3.601	3.902	9.575	5.380	17.006	3.598	6.931	4.069
		10		3.511	9.716	9.133	9.449	24.177	9.528	8.526	6.294	14.837	9.352	22.338	22.034	11.459	8.836
	$\Theta_{2t}^{(q1)}$	1		0.08	0.37	0.357	2.438	1.948	0.013	3.8**	59.1***	7.673	60.693	0.189	3.467	7.580	26.451
		5		5.160	2.738	2.406	4.114	3.306	7.514	10.531	65.9***	15.570	65.056	6.135	7.089	11.689	33.310
		10		6.245	15.509	9.538	6.080	12.663	10.804	16.129	74.2***	24.423	67.974	8.418	7.826	18.840	41.043
	$\Theta_{2t}^{(q2)}$	1		5.9***	2.196	4.046	0.055	0.736	2.998	7.1***	7.2***	1.143	7.319	0.136	0.31	2.763	13.268
		5		12.7**	12.327	6.186	4.135	1.835	9.453	11.5**	16.2***	12.836	16.876	3.774	7.038	4.341	18.440
		10		20.8**	29.454	11.243	6.599	8.208	17.075	19.6**	20.7**	14.008	18.565	6.260	10.350	7.501	28.454
	$\Theta_{2t}^{(q3)}$	1		3.142	1.010	4.352	0.129	6.330	0.28	0.121	0.257	18.870	3.501	1.659	2.103	0.1	1.508
		5		5.443	3.899	6.990	1.019	7.169	5.536	2.684	5.328	29.740	4.751	3.356	6.194	1.786	8.161
		10		7.807	10.916	8.856	5.948	13.173	10.311	5.405	14.908	32.002	14.736	5.278	11.750	4.843	14.905
	$\Theta_{2t}^{(q4)}$	1		0.002	0.544	0.504	0.992	0.317	1.353	0.05	7.9***	1.953	8.858	0.696	0.337	1.355	4.848
		5		4.061	3.558	6.195	3.395	5.626	7.289	3.104	15.4***	8.739	16.734	6.193	3.610	3.499	8.904
		10		7.196	6.306	9.987	5.420	9.267	10.685	7.031	18.3**	12.045	20.311	8.680	8.212	11.008	14.921
	$\Theta_{2t}^{(q5)}$	1		0.008	0.074	0.007	1.248	0.983	0.002	0.029	51.6***	1.134	59.547	4.184	0.155	2.673	37.799
		5		12.5**	6.430	6.053	2.164	10.8**	7.821	6.028	56.5***	3.028	64.510	9.237	5.002	10.072	38.757
		10		15.674	13.135	10.374	3.274	18.4**	10.988	8.725	60.0***	16.201	68.500	12.187	7.530	12.655	50.230

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

To sum up, as can be seen from Table 3.11 there exist negative contagion from S&P 500 and FTSE 100 to BIST 100. Moreover, there is a weak contagion from DAX 100 to BIST 100. However, the picture is different for the relationship between BIST 100 and NIKKEI 225. It can be stated that there is a weak volatility spillover from BIST 100 to NIKKEI 225 due to the causality in variance. But in the opposite direction NIKKEI 225 has no influence on BIST 100. Therefore, it may be suggested that NIKKEI 225 and DAX 100 are good diversification alternatives for investors investing in BIST 100.

Table 3.11 : Summary of Granger causality test results between BIST 100 and developed markets.

	Direction of causality	
Negative Contagion		S&P 500→BIST 100
Negative Contagion		DAX 100 →BIST 100 (weakly)
Negative Contagion		FTSE 100→BIST 100
Volatility spillover (causality in variance)	BIST 100→NIKKEI 225 (weakly)	

3.5.3 Granger causality tests in moments between BIST 100 and emerging markets

As can be seen from Table 3.12 we might conclude that the Argentina stock market index (MERVAL) could Granger-cause the Turkish stock market index (BIST 100) in mean but not in variance, and the Turkish stock market index (BIST 100) may weakly Granger-cause the Argentina stock market index (MERVAL) in mean. By setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q1)}$, $\Theta_{2t}^{(q1)}$), the G test statistic is significant for (y_{1t}, y_{2t}) = ($y_t^{BIST\ 100}$, y_t^{MERVAL}) suggesting that the left tail of the Argentina stock market index (MERVAL) distribution, could Granger cause the left tails of the Turkish stock market index (BIST 100). These results indicates that there exist contagion in falling stock market periods and regards BIST 100 as a spillover receiver.

Table 3.12 : G test Statistics for BIST 100 and MERVAL

				$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{MERVAL})$							$(y_{1t}, y_{2t}) = (y_t^{MERVAL}, y_t^{BIST\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**23.8*****	1.285	9.6***	5.9**	1.724	0.494	25.6***	0.134	1.236	1.263	0.008	1.562	0.346	0.158
		5		**26.8*****	7.444	15.5***	7.115	6.087	6.580	31.3***	12.6**	7.719	12.3**	3.104	3.415	3.805	10.8**
		10		**31.06*****	17.647	23.4***	13.127	12.576	17.509	38.2***	24.2***	15.637	15.644	8.593	7.632	9.501	27.3***
	$\Theta_{2t}^{(2)}$	1		2.616	0.947	0.035	0.721	0.009	0.481	6.04***	3.1*	0.493	7.8***	0.077	0.136	0.867	1.177
		5		9.9*	3.837	3.320	6.245	3.114	1.691	14.1***	7.785	8.815	16.4***	2.478	2.323	10.112	6.934
		10		20.5**	19.338	8.497	9.893	13.961	3.866	35.5***	10.426	16.698	20.9**	15.303	7.463	15.541	11.345
	$\Theta_{2t}^{(q1)}$	1		20.2***	0.086	**10.4*****	4.1**	3.8**	0.383	17.7***	0.065	0.389	0.16	0.627	0.026	0.345	0.12
		5		27.2***	5.206	**16.7*****	5.161	8.109	9.798	22.5***	6.579	7.946	4.730	3.255	2.520	7.963	8.920
		10		36.4***	14.107	**19.6****	7.627	15.786	14.640	42.4***	13.659	10.151	7.237	5.140	8.238	11.139	17.029
	$\Theta_{2t}^{(q2)}$	1		0.352	0.005	0.227	0.129	0.109	0.635	1.399	0.009	4.060	0.157	0.344	0.156	1.455	0.207
		5		1.449	7.781	3.188	0.728	2.304	5.417	6.535	11.400	7.778	7.271	10.430	0.808	2.740	9.784
		10		2.746	11.108	9.047	3.194	11.481	7.537	7.745	14.031	11.725	21.372	17.026	4.882	10.934	12.101
	$\Theta_{2t}^{(q3)}$	1		0.73	0.592	0.02	0.198	5.1**	4.7**	0.759	0.066	0.018	2.004	0.049	2.130	0.078	0.205
		5		3.537	7.120	3.943	2.359	7.451	5.228	5.071	8.403	2.439	6.333	1.859	6.464	3.315	4.025
		10		17.8**	17.505	16.849	6.945	12.422	6.920	11.519	15.999	4.261	11.329	4.053	14.232	12.193	14.851
	$\Theta_{2t}^{(q4)}$	1		10.7***	0.063	6.0***	2.555	0.275	0.57	9.8***	3.0*	1.209	0.024	0.001	3.075	0.049	1.838
		5		13.8***	8.117	9.3*	3.926	4.672	4.718	12.4***	14.2***	2.450	3.783	3.930	4.263	1.855	7.490
		10		17.2*	16.911	14.287	5.209	13.619	10.233	22.3***	16.7*	15.429	8.035	11.309	10.591	5.438	10.935
	$\Theta_{2t}^{(q5)}$	1		6.7***	0.692	3.203	2.012	0.069	0.001	6.4***	1.419	1.187	3.7**	0.004	0.006	0.142	1.950
		5		9.153	4.412	8.378	6.547	4.610	1.723	9..4*	5.845	5.456	11.1**	4.966	0.572	2.576	11.9**
		10		15.495	18.810	16.327	10.336	6.569	5.544	15.253	13.495	20.000	13.784	16.396	2.778	6.915	18.03**

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

When we analyze the causal relationship between Turkey and Brazil, we can see that there is a significant causal relationship from Brazilian stock market (BOVESPA) to Turkish stock market (BIST 100). The G test statistics are significant in mean, in variance and also in many parts of the distribution.

As can be seen from the Table 3.13, there exists Granger causality in mean and variance from BOVESPA to BIST 100. One may conclude that volatility spill over from Brazilian stock market to Turkish stock market.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t})= (y_t^{BIST\ 100}, y_t^{BOVESPA})$, suggesting that the left tail of Brazilian stock market index (BOVESPA) distribution, could Granger cause the left tails of Turkish stock market index (BIST 100).

In addition, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q5)})$, the G test statistic is significant for $(y_{1t}, y_{2t})= (y_t^{BIST\ 100}, y_t^{BOVESPA})$, suggesting that the right tail of Brazilian stock market index (BOVESPA) distribution, could Granger cause the right tail of Turkish stock market index (BIST 100). However, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q3)}, \Theta_{2t}^{(q3)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}\ y_t^{BOVESPA})$ suggesting that the center of Brazilian stock market index (BOVESPA) distribution could Granger cause the center of Turkish stock market (BIST 100) distribution.

Therefore, one may conclude that BIST 100 is dependent on Brazilian stock market index (BOVESPA) by the reason of significant Granger causality in the center of the distributions.

Table 3.13 : G test Statistics for BIST 100 and BOVESPA.

Granger causality in moments			$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{BOVESPA})$							$(y_{1t}, y_{2t}) = (y_t^{BOVESPA}, y_t^{BIST\ 100})$						
Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
$\Theta_{2t}^{(1)}$	1		**83.2*** **	0.015	54.3***	14.6***	0.798	1.094	82.2***	0.606	0.527	0.147	0.365	0.161	0.436	0.489
	5		**91.2*** **	1.990	59.9***	16.6***	5.082	7.201	85.2***	1.910	3.302	2.627	6.556	0.697	1.667	2.838
	10		**94.9*** **	16.839	64.9***	20.5**	17.248	21.7***	97.3***	4.105	11.575	9.961	10.407	10.284	9.495	3.949
$\Theta_{2t}^{(2)}$	1		1.455	**7.1*** **	3.6**	0.087	5.5***	1.781	0.669	0.166	2.404	0.538	0.901	0.215	1.306	0.24
	5		4.828	**15.6*** **	11.6**	9.290	12.3**	10.6**	2.821	3.014	7.598	5.072	8.821	4.821	3.765	5.776
	10		10.001	**21.4*** **	16.1*	10.392	17.6*	14.881	4.298	3.846	18.709	5.561	11.809	9.632	24.2***	11.279
$\Theta_{2t}^{(q1)}$	1		49.2***	1.877	**31.6*** **	3.808	3.5**	0.789	32.2***	0.462	0.586	0.073	2.031	0.002	0.231	2.027
	5		58.6***	8.202	**33.1*** **	7.229	6.569	7.756	36.5***	1.809	1.341	0.981	7.168	3.573	2.567	7.505
	10		603***	16.672	**33.3*** **	14.149	17.716	20.6**	51.2***	6.587	5.565	7.541	9.079	12.887	15.968	8.913
$\Theta_{2t}^{(q2)}$	1		3.3*	4.8**	8.06***	0.038	0.279	0	7.2***	0.285	0	0.582	0.282	0.12	3.232	0.252
	5		11.8**	6.588	9.223	4.065	3.176	1.098	14.1***	7.892	1.360	8.824	3.849	1.783	4.339	2.961
	10		17.5*	18.1**	11.547	25.031	9.063	7.363	22.2***	10.741	4.489	10.247	5.590	8.413	10.406	7.125
$\Theta_{2t}^{(q3)}$	1		0.111	2.151	2.489	1.288	**4.2** **	0.291	1.011	0.029	2.283	1.793	1.844	0.894	0.423	1.399
	5		4.091	5.413	4.025	5.564	**13.2** **	2.042	2.848	5.010	4.688	10.156	10.345	6.131	9.801	3.655
	10		4.820	10.100	16.834	13.866	**25.8*** **	5.017	7.815	6.326	9.908	14.198	17.526	16.711	13.467	5.844
$\Theta_{2t}^{(q4)}$	1		1.882	0.605	2.858	1.052	3.271	0.538	1.683	0.006	0.065	0.119	5.1**	2.156	0.176	0.216
	5		5.634	2.406	8.022	2.733	4.742	7.388	6.094	6.909	11.099	6.720	12.6**	6.418	4.152	8.966
	10		7.169	4.437	13.315	7.170	10.151	12.297	10.843	7.180	19.207	8.636	15.825	11.552	12.174	13.187
$\Theta_{2t}^{(q5)}$	1		60.6***	0.002	40.6***	6.1***	1.752	3.5**	**43.7*** **	0.792	0.174	1.874	1.164	0.011	1.484	0.341
	5		66.9***	1.373	47.1***	10.5*	8.387	8.795	**47.1*** **	4.415	6.583	11.5**	9.014	1.726	6.042	3.050
	10		68.9***	18.783	53.8***	19.7**	14.332	20.8**	**49.8*** **	7.007	13.704	18.3***	12.813	10.977	10.675	8.661

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.14 we might conclude that the Mexican stock index (IPC) could Granger-cause the Turkish stock market index (BIST 100) in mean, and the Turkish stock market index (BIST 100) may weakly Granger-cause the Mexican stock index (IPC) in mean. In addition, the G test statistic for hypothesis of no causality in variance is significant with n = 1 but insignificant for all the other cases being considered. Therefore the Mexican stock index (IPC) could weakly Granger-cause the Turkish stock market index (BIST 100) in variance and the Turkish stock market index (BIST 100) may Granger-cause the Mexican stock index (IPC) in mean but not in variance.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{IPC})$ suggesting that the left tail of Mexican stock index (IPC), could Granger cause the left tails of Turkish stock market index (BIST 100). These results indicates that there exist contagion in falling stock market periods and regards BIST 100 as a spillover receiver.

Table 3.14 : G test Statistics for BIST 100 and IPC.

			$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{IPC})$							$(y_{1t}, y_{2t}) = (y_t^{IPC}, y_t^{BIST\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1	**71.2*** **	0.233	59.4***	6.6***	1.978	5.8***	50.7***	5.3**	0.13	7.219	2.002	2.302	0.206	4.3**
		5	**73.8*** **	6.449	63.2***	8.018	3.489	10.9**	54.4***	7.802	4.106	8.744	4.459	5.607	8.850	5.723
		10	**80.4*** **	18.928	66.3***	10.540	13.278	23.2***	64.9***	11.030	8.659	10.734	10.227	10.310	19.599	13.105
	$\Theta_{2t}^{(2)}$	1	7.2***	2.749	**4.6** **	0.293	2.472	0.027	2.779	0.553	0.895	0.11	0.151	0.143	0.041	0.075
		5	12.3**	5.790	10.516	4.329	3.338	8.559	3.500	3.429	11.178	7.253	9.383	3.647	2.638	3.505
		10	18.0**	7.636	16.181	5.959	7.931	10.706	10.152	8.395	17.886	15.348	14.238	9.731	9.194	5.528
	$\Theta_{2t}^{(q1)}$	1	60.09***	0.134	**38.7*** **	3.211	1.011	1.544	50.2***	6.2***	0.533	4.237	1.857	1.530	0.495	8.5***
		5	68.8***	3.488	**45.6*** **	6.860	4.387	3.715	57.7***	8.098	5.124	4.788	5.397	8.407	5.130	9.827
		10	71.1***	12.590	**47.6*** **	8.388	12.589	6.277	65.6***	19.8**	7.940	17.023	9.152	10.654	20.157	19.8**
	$\Theta_{2t}^{(q2)}$	1	0.001	0.715	1.837	0.079	0.049	5.0**	0.158	0.226	0.26	0.31	0.08	0.019	1.927	0.091
		5	4.089	2.996	7.002	6.670	2.064	5.573	2.869	3.847	3.648	1.825	4.029	1.373	4.271	4.614
		10	14.906	8.886	9.987	8.546	2.240	21.081	22.817	6.075	5.134	6.831	9.893	9.949	16.251	6.660
	$\Theta_{2t}^{(q3)}$	1	0.022	9.5***	1.856	0.953	0.093	0.004	0.036	0.431	2.296	0.004	0.179	0.015	3.250	1.788
		5	9.136	14.1***	5.456	2.286	2.008	4.133	3.474	3.786	5.376	4.472	3.633	9.742	5.504	7.110
		10	11.714	19.6**	11.224	8.302	3.567	11.914	6.730	6.582	15.241	6.776	11.804	13.503	9.539	11.897
	$\Theta_{2t}^{(q4)}$	1	2.223	1.234	1.494	2.968	0.028	1.501	1.787	0.004	0.313	0.045	1.242	0.002	0.291	0.502
		5	8.398	3.728	6.706	4.996	2.440	5.727	4.026	2.677	12.477	5.001	4.186	1.712	1.281	1.327
		10	16.892	10.717	15.849	12.431	7.022	10.948	16.789	4.696	17.185	11.225	12.074	4.185	14.286	5.011
	$\Theta_{2t}^{(q5)}$	1	35.3***	0.845	35.5***	2.147	0.472	3.693	15.8***	4.614	0.799	5.642	1.151	1.362	2.359	0.346
		5	37.1***	10.9***	37.2***	3.334	1.380	5.177	20.05***	8.753	6.219	9.668	7.560	6.829	14.5***	3.040
		10	44.7***	27.2***	42.5***	11.641	6.829	14.896	31.1***	13.121	16.488	11.820	16.212	12.928	24.9***	11.241

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

When we analyze the causal relationship between Turkey and Chile, we can see that there is a significant causal relationship from Chile stock market index (IPSA) to Turkish stock market index (BIST 100). We can see from the Table 3.15 that the Chile stock market index (IPSA) could Granger-cause the Turkish stock market index (BIST 100) in mean but not in variance, and the Turkish stock market index (BIST 100) may weakly Granger-cause the Chile stock market index (IPSA) in mean.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{IPSA})$ suggesting that the left tail of the Chile stock market index (IPSA), could Granger cause the left tails of the Turkish stock market index (BIST 100). However, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q3)}, \Theta_{2t}^{(q3)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}\ y_t^{IPSA})$ suggesting that the center of the Chile stock market index (IPSA) distribution could Granger cause the center of Turkish stock market (BIST 100) distribution.

Therefore, one may conclude that BIST 100 is dependent on the Chile stock market index (IPSA) by the reason of significant Granger causality in the center of the distributions.

Table 3.15 : G test Statistics for BIST 100 and IPSA.

			$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{IPSA})$							$(y_{1t}, y_{2t}) = (y_t^{IPSA}, y_t^{BIST\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1	**31.4*** **	0.234	19.7***	3.7**	0.247	4.3**	23.7***	7.2***	0.733	8.2***	0.06	0.018	0.022	6.01***
		5	**38.4*** **	2.883	27.3***	9.198	7.376	11.9**	25.8***	8.886	2.781	12.1**	2.372	1.232	2.940	8.298
		10	**39.1*** **	17.680	30.4***	11.385	19.922	18.5**	29.5***	38.5***	7.049	26.9***	8.636	5.935	8.912	26.8***
	$\Theta_{2t}^{(2)}$	1	3.062	0.345	1.147	0.39	0.051	1.144	3.9**	0.02	0.098	0.293	0.153	0.116	0.018	0.272
		5	5.429	12.4**	5.295	2.333	21.5***	2.770	6.169	7.961	5.158	3.930	1.352	3.337	1.809	7.745
		10	7.326	19.1**	11.074	2.876	29.2***	6.855	12.847	16.474	12.518	14.061	9.009	6.292	4.096	18.1**
	$\Theta_{2t}^{(q1)}$	1	21.4***	0.226	**10.3*** **	0.451	1.199	1.141	16.4***	6.1***	0.155	5.429	1.028	1.062	0.095	4.1**
		5	32.8***	9.699	**13.8*** **	4.966	3.563	7.332	20.5***	7.364	3.672	8.890	4.157	10.192	5.173	6.323
		10	34.6***	22.08***	**19.01** **	7.591	9.645	16.828	29.4***	29.8***	6.346	26.3***	8.732	15.912	7.507	19.3**
	$\Theta_{2t}^{(q2)}$	1	4.3**	0.174	5.4**	1.609	0.207	1.904	4.02**	3.364	0.363	4.9**	0.005	0.206	1.360	0.678
		5	6.254	3.633	9.359	6.352	5.831	2.762	5.247	6.177	6.282	6.261	8.016	10.896	5.634	9.268
		10	13.205	4.630	10.908	8.788	12.519	15.479	8.806	10.840	13.063	16.205	13.002	24.274	10.891	11.120
	$\Theta_{2t}^{(q3)}$	1	1.172	4.4**	0.41	0.444	**4.5** **	5.4**	1.136	2.161	2.230	2.127	0.006	0.285	0	0.538
		5	1.579	10.032	2.403	2.266	**12.4** **	7.940	2.194	2.928	14.055	5.365	4.047	5.136	4.004	3.213
		10	6.131	14.083	5.691	4.392	16.108	14.368	2.821	8.235	18.864	7.807	8.030	7.559	6.145	13.837
	$\Theta_{2t}^{(q4)}$	1	6.2***	0.417	3.8**	1.325	0.047	0.536	2.293	0	2.570	0.148	5.829	1.748	0.886	0.068
		5	20.06***	1.382	8.743	6.420	5.268	5.153	7.805	8.696	5.203	6.249	7.825	3.680	8.342	2.431
		10	25.6***	3.960	10.528	23.2***	8.353	12.306	15.758	12.547	14.689	7.742	12.979	4.376	15.576	10.340
	$\Theta_{2t}^{(q5)}$	1	8.6***	0.36	11.1***	5.5***	0.304	8.3***	7.8***	8.02***	2.734	8.2***	0.596	0.063	0.228	2.823
		5	10.5*	3.504	20.7***	15.2***	9.776	12.9**	9.834	9.320	9.060	12.5**	0.763	3.972	4.172	3.565
		10	14.221	7.521	24.6***	17.4*	20.6**	17.3*	15.207	33.4***	12.981	28.1***	4.765	6.878	20.115	21.670

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.16 we might conclude that Colombia stock market index (COLCAP) could Granger-cause the Turkish stock market index (BIST 100) in variance. This result specify that there exists volatility spillovers from Colombia stock market to Turkish stock market. However, Turkish stock market index (BIST 100) may not Granger-cause Colombia stock market index (COLCAP) index in variance.

In addition, we could not find any causal relationship between the tails of stock market index distributions. Therefore I couldn't find any evidence of financial contagion between Turkey and Colombia.

Table 3.16 : G test Statistics for BIST 100 and COLCAP.

				$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{COLCAP})$							$(y_{1t}, y_{2t}) = (y_t^{COLCAP}, y_t^{BIST\ 100})$						
Granger causality in moments	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
	$\Theta_{2t}^{(1)}$	1		0.947	0.265	1.474	0.216	0.194	1.630	0.001	1.372	0.068	0.001	0.016	0.023	1.597	1.038
		5		4.742	5.540	2.433	3.443	7.084	4.817	4.197	5.358	1.083	5.110	3.427	6.109	11.090	4.626
		10		7.199	12.368	7.747	9.400	11.977	8.774	5.788	9.526	3.165	8.742	4.177	8.529	13.368	6.596
	$\Theta_{2t}^{(2)}$	1		2.473	**6.855*** **	2.540	0.077	0.015	0.023	1.235	3.441*	0.026	4.067**	1.519	3.067	0.011	0.715
		5		10.246	**13.627*** **	8.248	2.991	2.649	1.969	3.466	11.77***	3.099	16.78***	4.218	5.817	3.389	8.651
		10		13.162	**17.455** **	8.097	8.001	7.090	9.883	8.305	19.3***	7.525	28.06***	8.710	9.177	12.569	15.036
	$\Theta_{2t}^{(q1)}$	1		0.107	0.063	0.077	0.664	0.823	1.011	0.242	0.724	1.531	0.024	0.774	0.164	0.369	0.052
		5		6.423	4.214	3.463	2.447	15.241	4.182	8.365	4.984	4.792	2.965	2.317	11.749	12.421	3.618
		10		6.951	9.304	11.898	12.962	21.709	6.937	11.108	12.170	6.214	16.735	3.003	15.087	14.275	7.935
	$\Theta_{2t}^{(q2)}$	1		1.485	0.207	0.775	0.261	0.168	0.121	0.123	1.984	1.489	0.028	1.343	0.161	0.045	1.957
		5		7.749	2.425	1.613	1.242	6.681	7.910	2.761	5.718	4.441	2.278	2.337	2.404	5.696	9.597
		10		12.475	4.498	3.957	9.747	10.570	8.080	5.365	10.654	13.803	9.581	6.664	3.629	14.457	18.007
	$\Theta_{2t}^{(q3)}$	1		0.226	0.369	0.559	0.001	0.357	0.071	1.180	0.023	1.158	1.409	3.006	0.285	0.182	0.042
		5		2.544	3.165	3.398	0.221	2.991	2.272	4.897	6.088	9.068	5.060	6.125	5.814	3.935	6.444
		10		5.472	5.964	6.270	4.452	12.281	6.427	6.540	7.235	20.257	7.128	8.595	6.995	5.968	10.149
	$\Theta_{2t}^{(q4)}$	1		0.837	0.51	0.085	0.438	0.546	0.053	2.583	0.783	0.887	1.973	2.626	1.953	0.054	1.395
		5		6.296	6.939	3.909	4.211	7.115	1.089	8.008	6.563	5.834	4.558	3.443	5.531	4.325	2.741
		10		7.689	7.354	9.321	9.876	10.759	10.660	11.765	13.207	11.006	10.857	5.370	6.215	6.108	8.564
	$\Theta_{2t}^{(q5)}$	1		0.263	0.108	1.297	0.087	0.163	1.069	0.061	1.479	0.063	0.005	0.043	0.001	0.861	0.575
		5		5.397	2.718	6.888	0.364	9.127	4.202	7.007	6.076	2.264	3.369	4.555	1.341	9.127	6.827
		10		7.739	4.790	9.408	4.640	18.553	15.788	9.744	11.264	5.731	7.134	6.626	5.707	9.999	9.366

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.17 we might conclude that the Turkish stock market index (BIST 100) could Granger-cause the Indonesian stock market index (IDX) in mean, and in variance. On the other hand, the Indonesian stock market index (IDX) may Granger-cause the Turkish stock market index (BIST 100) neither in mean nor in variance.

By setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q1)}$, $\Theta_{2t}^{(q1)}$), the G test statistic is significant for (y_{1t}, y_{2t}) = (y_t^{IDX}, $y_t^{BIST\ 100}$) suggesting that the left tail of Turkish stock market index (BIST 100), could Granger cause the left tails of Indonesian stock market index (IDX). These results indicates that there exist contagion in falling stock market periods and regards BIST 100 as a driver of spillover.

Table 3.17 : G test Statistics for BIST 100 and IDX.

		$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{IDX})$							$(y_{1t}, y_{2t}) = (y_t^{IDX}, y_t^{BIST\ 100})$						
Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments															
$\Theta_{2t}^{(1)}$	1	1.255	0.001	0.217	0.001	0.077	0.865	0.967	**35.06*** **	2.638	28.1***	1.821	1.315	0.144	30.8***
	5	3.880	4.424	7.670	3.990	1.470	8.988	2.770	**46.6*** **	5.263	33.7***	5.204	4.368	3.270	39.7***
	10	6.694	16.480	12.856	6.209	3.329	24***	7.477	**55.2*** **	9.483	41.3***	10.471	6.876	6.270	48.8***
$\Theta_{2t}^{(2)}$	1	0.064	2.627	0.435	2.095	3.670	0.028	3.179	1.329	**6.8*** **	4.1**	0.139	5.3***	1.071	0.802
	5	2.073	14.636	6.294	13.528	6.237	5.722	5.554	11.3**	**15.2*** **	8.230	10.709	20.7***	2.581	8.820
	10	7.598	16.293	8.052	19.272	11.707	9.697	10.003	12.411	16.641	9.598	11.987	26.0***	4.620	12.189
$\Theta_{2t}^{(q1)}$	1	1.228	2.122	3.086	0.122	3.279	0.796	0.431	31.0***	6.3***	**30.7*** **	1.630	3.179	1.612	**16.9*** **
	5	4.448	3.720	6.450	7.797	7.006	9.613	5.035	33.8***	8.310	**35.1*** **	6.042	11.8**	3.773	**22.2*** **
	10	7.334	11.544	10.537	17.059	8.489	23.9***	8.949	43.5***	15.226	**43.5*** **	11.022	16.950	13.451	**30.5*** **
$\Theta_{2t}^{(q2)}$	1	0.091	0.045	0.023	0.008	3.064	0.344	0.813	6.3***	2.993	0.73	4.998	0.467	0.012	5.7***
	5	3.157	2.650	0.393	2.269	8.788	13.778	2.126	14.1***	6.806	2.975	11.201	1.553	8.860	12.7***
	10	6.800	4.087	10.104	6.450	14.898	23.589	3.857	16.084	8.236	6.982	21.169	7.241	12.680	17.529
$\Theta_{2t}^{(q3)}$	1	0.015	8.3***	5.360	0.323	22.7***	2.110	3.263	1.224	0.036	2.574	5.087	6.6***	0.001	0.428
	5	2.112	11.4**	9.037	3.109	27.4***	2.885	6.459	5.729	2.366	8.352	6.798	13.3**	8.045	2.877
	10	5.453	23.4***	11.948	10.688	33.6***	5.647	9.971	11.466	5.265	11.075	10.063	17.150	15.670	10.960
$\Theta_{2t}^{(q4)}$	1	0.098	1.080	0.048	1.741	0.155	0.098	0.13	6.4***	24.01***	6.01***	0.346	0.576	4.239	0.136
	5	12.060	19.7***	2.307	2.982	5.314	1.989	10.039	10.8**	30.1***	18.6***	3.911	7.168	5.424	0.725
	10	13.043	28.3***	8.114	10.324	9.099	2.865	11.533	14.867	36.6***	23.9***	7.907	12.336	14.422	4.825
$\Theta_{2t}^{(q5)}$	1	2.089	1.686	0.287	1.951	2.561	0.079	3.116	24.2***	0.374	11.4***	3.718	0.212	0.551	20.5***
	5	6.666	12.09**	6.998	6.082	8.483	4.137	5.034	33.01***	1.758	14.7***	6.746	9.367	6.937	27.7***
	10	9.775	25.8***	16.693	8.186	13.609	14.886	8.182	35.9***	2.339	16.975	8.429	14.940	9.566	33.5***

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

From the analysis of other country pair in Table 3.18 we may conclude that the Indian stock market index (S&P BSE SENSEX) may Granger-cause the Turkish stock market index (BIST 100) in mean but not in variance, and also the Turkish stock market index (BIST 100) may Granger-cause Indian stock market index (S&P BSE SENSEX) in mean but not in variance. By setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q1)}$, $\Theta_{2t}^{(q1)}$), the G test statistic is significant for (y_{1t}, y_{2t}) = ($y_t^{BIST\ 100}$, y_t^{SENSEX}) with n = 1,5 suggesting that the left tail of Indian stock market index (S&P BSE SENSEX), could Granger cause the left tails of the Turkish stock market index (BIST 100). Additionally, By setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q1)}$, $\Theta_{2t}^{(q1)}$), the G test statistic is significant for (y_{1t}, y_{2t}) = (y_t^{SENSEX} $y_t^{BIST\ 100}$) suggesting that the left tail of the Turkish stock market index (BIST 100) could Granger cause the left tails of the Indian stock market index (S&P BSE SENSEX). These results indicates that there exist contagion in falling stock market periods and regards generally bilateral. An extreme downside risk from one stock market has a predictive content for an extreme downside risk for another.

Table 3.18 : G test Statistics for BIST 100 and SENSEX.

				$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{SENSEX})$							$(y_{1t}, y_{2t}) = (y_t^{SENSEX}, y_t^{BIST\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**8.7*** **	0.066	7.1***	0.175	1.678	0.002	1.281	**24.7*** **	0.284	18.3***	6.5***	0.133	7.4***	16.8***
		5		**15.1*** **	9.019	10.9**	4.130	9.989	4.507	11.3**	**31.4*** **	2.996	23.0***	11.5**	1.693	9.268	22.03***
		10		16.722	30.141	14.651	5.781	18.854	14.891	24.1***	**46.7*** **	22.4***	26.9***	22.6***	5.412	12.355	43.2***
	$\Theta_{2t}^{(2)}$	1		0.778	1.265	0.653	0.131	0	2.413	0.007	5.5***	1.408	1.673	0.538	0.028	6.3***	0.726
		5		6.862	4.274	3.654	3.408	10.589	3.447	7.719	9.915	10.406	3.622	1.996	9.084	15.4***	6.888
		10		11.615	15.142	9.445	10.701	12.870	12.152	11.123	14.060	17.598	6.043	3.516	23.257	35.4***	12.268
	$\Theta_{2t}^{(q1)}$	1		5.5***	0.126	**4.2** **	0.483	4.313	0.579	0.055	18.7***	0.233	**13.9*** **	6.09***	0.925	5.2**	**11.3*** **
		5		14.7***	5.592	**11.09** **	6.206	7.490	5.967	7.780	21.5***	3.318	**17.3*** **	11.8**	5.732	14.1***	**11.5** **
		10		16.908	6.902	**15.354**	9.735	13.797	11.947	10.881	32.8***	14.214	**21.9*** **	17.416	16.562	26.9***	**19.1** **
	$\Theta_{2t}^{(q2)}$	1		0.918	0.668	2.265	3.744	0.772	0.048	0.761	4.4**	0.043	0.813	0.445	0.123	0.453	6.1***
		5		4.007	5.539	5.257	6.045	2.231	7.166	4.753	17.1***	1.859	11.5**	5.325	5.061	4.731	18.7***
		10		13.532	15.932	8.527	9.398	3.716	12.669	14.024	19.4**	4.088	15.560	7.461	10.174	12.6**	26.7***
	$\Theta_{2t}^{(q3)}$	1		0.035	0.791	0.336	0.045	1.263	0.003	0.056	1.612	2.945	0.479	1.459	1.259	0.245	1.030
		5		4.772	5.836	2.082	10.559	6.382	10.6**	2.034	2.959	5.547	2.541	3.519	2.484	12.379	3.930
		10		11.487	20.5**	11.991	20.333	7.385	17.8**	18.497	4.819	8.564	4.067	7.531	13.693	19.540	10.695
	$\Theta_{2t}^{(q4)}$	1		1.328	11.04***	7.756	1.254	0.186	2.853	0.112	8.7***	3.607	3.7**	0.809	0.091	0.446	2.554
		5		3.938	14.6***	11.511	5.418	8.200	6.553	1.783	13.1**	15.6***	12.9**	1.628	4.898	5.949	3.896
		10		7.858	22.9***	16.790	12.219	10.110	9.282	5.491	18.5**	28.8***	18.02**	11.125	10.003	10.405	11.430
	$\Theta_{2t}^{(q5)}$	1		3.779	0.969	0.318	0.019	0.096	0.922	2.105	6.3***	1.928	6.3***	1.682	0.454	1.855	7.3***
		5		8.863	6.615	0.616	2.726	9.164	3.353	12.4**	9.888	6.383	7.678	2.977	4.767	6.925	19.5***
		10		12.781	34.7***	11.126	9.065	15.300	18.602	26.6***	22.3***	18.1***	9.127	10.470	10.773	13.387	38.6***

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

Finally, From Table 3.19, we might conclude that FTSE Bursa Malaysia KLCI index could Granger-cause the Turkish stock market index (BIST 100) in variance, and likewise Turkish stock market index (BIST 100) Granger-cause FTSE Bursa Malaysia KLCI index in variance. Hence, the evidence showed that there exist bilateral volatility spillovers.

But it could not find any causal relationship between the tails of stock market index distribution.

Table 3.19 : G test Statistics for BIST 100 and KLCI.

Granger causality in moments			$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{KLCI})$							$(y_{1t}, y_{2t}) = (y_t^{KLCI}, y_t^{BIST\ 100})$						
Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
$\Theta_{2t}^{(1)}$	1		0.325	2.319	0.01	0.175	0.492	3.145	0.287	0.042	0.201	0.046	0.156	0	0.52	0.022
	5		2.830	3.112	0.991	2.183	0.798	5.909	3.587	2.615	8.037	7.185	7.079	2.505	5.259	4.179
	10		11.040	5.511	4.205	4.762	15.422	13.155	17.684	6.679	13.438	12.534	16.709	3.379	11.587	7.678
$\Theta_{2t}^{(2)}$	1		0.545	**4.496****	8.433	2.899	0.077	0.146	0.159	2.288	**7.889*****	2.732	0.044	2.266	2.172	0.593
	5		2.576	**13.545****	10.447	4.327	2.446	2.890	2.506	10.612	**20.163*****	10.038	7.380	8.281	5.774	8.415
	10		5.697	**27.118****	15.636	6.367	6.190	10.459	11.782	17.328	**27.895*****	20.486**	8.231	10.698	14.919	17.359
$\Theta_{2t}^{(q1)}$	1		2.017	4.225**	3.968	0.443	0.147	0.959	0.481	0	0.075	0.23	0.002	0.129	0.203	0.205
	5		4.698	5.836	6.215	2.498	3.458	7.397	4.862	0.562	12.361	5.412	5.001	3.389	6.155	4.642
	10		9.512	14.448	12.495	4.025	8.385	10.503	10.141	8.987	19.524	13.655	12.555	6.643	10.216	9.891
$\Theta_{2t}^{(q2)}$	1		0.204	0.636	0.156	0.478	0.006	0.161	0.003	0.212	0.001	0.189	1.757	0.481	0.774	0.539
	5		3.827	2.305	3.428	1.100	1.212	2.814	1.873	1.867	1.728	1.848	4.154	3.114	3.999	1.686
	10		8.702	7.169	7.470	6.362	6.154	4.767	12.313	15.723	2.376	4.708	8.160	9.317	8.370	14.621
$\Theta_{2t}^{(q3)}$	1		3.106	0.059	3.710	0.158	0.063	0.035	3.865	4.851	0.827	1.484	0.855	0.571	0.019	2.310
	5		4.903	2.151	6.362	3.392	13.494	1.961	7.095	6.748	2.932	3.946	6.196	2.864	1.010	3.430
	10		19.481	8.658	10.374	16.017	17.548	7.517	26.326	10.540	17.197	10.177	13.641	6.108	8.929	7.700
$\Theta_{2t}^{(q4)}$	1		0.537	1.301	0.808	0.565	0.026	0.084	0.386	0.357	0.435	0.117	0.018	2.390	2.075	0.042
	5		1.180	4.025	0.996	1.063	1.971	1.147	2.651	1.799	3.490	2.612	1.994	7.208	4.500	0.735
	10		11.196	5.213	13.602	6.928	11.306	3.661	5.029	3.495	9.856	8.529	5.636	16.444	7.482	8.116
$\Theta_{2t}^{(q5)}$	1		0.915	0.264	3.037	1.389	0	3.755	4.001	1.297	2.477	0.585	0.016	0.188	0.452	0.15
	5		2.374	1.873	5.494	3.008	6.152	6.254	5.999	5.360	3.199	4.738	2.078	1.995	2.449	4.907
	10		11.154	10.978	8.049	6.841	11.795	15.415	21.210	11.655	4.580	11.727	5.853	3.840	11.329	11.858

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As a summary in Table 3.20, there exists negative contagion from IPC and MERVAL to BIST 100. Having said that, it can be stated that BIST 100 is dependent on BOVESPA and IPSA by the reason of significant Granger causality in the center of the distributions. In addition, one way volatility spillover effect is observed from COLCAP to BIST 100. Furthermore, it can be seen that there is one way negative contagion from BIST 100 to IDX. In addition, there exist bilateral negative contagion between BIST 100 and SENSEX. Finally, there is bilateral volatility spillover between BIST 100 and MALAYSIA KLCI.

Table 3.20 : Summary of Granger causality test results between BIST 100 and emerging markets.

Direction of causality		
Negative Contagion		IPC→BIST 100
Negative Contagion		MERVAL→BIST 100
Strong Dependence		BOVESPA→BIST 100
Strong Dependence		IPSA→BIST 100
Volatility spillover (causality in variance)		COLCAP→BIST 100
Negative Contagion	BIST 100→IDX	
Negative Contagion	BIST 100→SENSEX	SENSEX→BIST 100
Volatility spillover (causality in variance)	BIST 100→ KLCI	KLCI→BIST 100

3.5.4 Granger causality tests in moments between U.S. two year bond yield and developed stock market indices

In order to test for contagion, flight to quality, and flight from quality, $(y_{1t}, y_{2t}) = (y_t^s, y_t^b)$ was set for exploring whether and how the bond return Granger causes the stock return, and $(y_{1t}, y_{2t}) = (y_t^b, y_t^s)$ was set for examining whether and how the stock return Granger causes the bond return. As mentioned before, flight to quality may be defined as an outflows of capital from the stock markets to the bond markets. And consistent with this definition, for each couple of asset returns (stock, bond) Granger-causality was tested from the left-tail distribution of stocks return to the right-tail distribution of bond return. Additionally, causality from the left tail of bond return distribution to the right tail of stock return distribution may be interpreted as flight from quality effect.

As can be seen from Table 3.21, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(1)}, \Theta_{2t}^{(1)})$, $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, and $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q5)})$ the G test statistics are significant for $(y_{1t}, y_{2t}) = (y_t^{NIKKEI\ 225}\ y_t^{USB})$ indicating respectively that there exists Granger causality from U.S. two year bond yield (USGG2YR) to Japan stock market index (NIKKEI

225) in mean, in left tails of the distributions, and from right tail of U.S. two year bond yield (USGG2YR) to the left tail of Japan stock market index (NIKKEI 225). It can be observed from the significance of the test statistics that that there is a strong relationship between Japan stock market index (NIKKEI 225) and U.S. two year bond yield (USGG2YR). Due to causality between left tails of these two distributions it may be clarified that there exist contagion from U.S. bond market to Japan stock market. On the other side, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(1)})$, the G test statistic with n=1 is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{NIKKEI\ 225})$ implying that the mean of Japan stock market index (NIKKEI 225) may weakly Granger cause the left tail of U.S. two year bond yield (USGG2YR). We may interpret this situation that Japan stock market has a week influence on U.S. bond market only during bear bond market conditions.

Table 3.21 : G test Statistics for U.S. bond yield and NIKKEI 225.

			$(y_{1t}, y_{2t}) = (y_t^{NIKKEI\ 225}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{NIKKEI\ 225})$						
Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments																
$\Theta_{2t}^{(1)}$	1		**20.9*** **	0.022	13.8***	2.123	0.896	5.1**	4**	0.04	3.499	**5.8*** **	2.871	0.554	4.196	2.633
	5		**127.6*** **	7.599	120.2***	5.968	4.274	17.5***	62.0***	2.475	7.599	7.537	4.385	4.032	5.329	4.980
	10		**132.3*** **	13.751	123.2***	8.626	11.822	26.2***	67.4***	9.342	14.678	10.813	13.602	10.900	15.145	10.077
$\Theta_{2t}^{(2)}$	1		0.669	0.087	0.402	0.74	0.012	1.773	0.933	0	0.854	0.361	3.264	0.952	2.671	0.03
	5		7.078	10.066	14.8***	13.607	9.151	6.797	13.180	3.545	2.692	1.547	12.746	3.141	4.549	1.911
	10		10.131	14.563	26.8***	18.154	10.392	16.840	16.357	17.034	11.350	13.906	18.319	5.719	6.598	8.249
$\Theta_{2t}^{(q1)}$	1		13.1***	0.055	**11.4*** **	1.781	5.01**	2.857	1.360	0.152	0.144	0.85	2.445	0.001	1.405	2.467
	5		94.7***	7.694	**84.5*** **	4.475	9.858	14.943	29.056	1.505	9.758	6.344	7.981	5.841	1.746	4.075
	10		98.2***	16.161	**90.9*** **	10.869	28.775	20.209	30.590	6.158	13.206	7.001	15.469	10.468	13.821	11.301
$\Theta_{2t}^{(q2)}$	1		0.365	0.323	0.234	0.008	1.610	0.044	0.51	0.755	0.384	0.287	2.685	1.042	1.515	0.013
	5		0.897	4.908	2.913	4.945	6.263	2.864	7.908	3.381	1.641	5.649	10.654	5.823	9.847	2.403
	10		7.822	8.421	10.054	7.887	13.978	3.946	15.585	6.071	6.657	8.155	17.840	7.360	12.250	8.099
$\Theta_{2t}^{(q3)}$	1		0	0.389	0.061	5.957	2.202	1.177	0.339	0	0.228	0.188	1.372	0.08	0.888	0.002
	5		3.787	1.048	3.216	8.153	6.587	2.704	5.934	3.620	4.755	6.133	7.971	8.184	3.355	7.089
	10		7.545	14.224	5.556	12.061	9.882	4.091	7.876	7.776	7.782	9.306	17.084	11.177	16.051	9.612
$\Theta_{2t}^{(q4)}$	1		5.5***	0.526	2.709	1.303	0.094	1.166	2.634	0.156	0.45	0.037	0.052	0.016	0.06	0.007
	5		17.9***	8.226	14.999	1.840	3.986	4.268	9.564	5.890	7.480	4.079	10.102	16.168	0.531	6.848
	10		19.0***	11.341	22.895	3.671	9.843	8.424	15.241	10.796	16.542	7.382	21.365	21.790	4.422	8.778
$\Theta_{2t}^{(q5)}$	1		4.5**	0.123	**3.8** **	0.105	0.059	2.892	0.678	0.005	5.6***	4.199	1.478	1.689	1.086	2.116
	5		71.4***	3.659	**68.3*** **	4.487	0.425	19.456	29.772	1.609	8.064	5.253	4.383	5.463	4.360	4.029
	10		78.0***	9.652	**70.1*** **	6.699	1.282	25.613	36.352	4.726	16.124	10.518	6.620	9.858	6.585	6.040

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.22 we might conclude that there is a strong relationship between German stock market index (DAX 100) and U.S. two year bond yield (USGG2YR). By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(1)}, \Theta_{2t}^{(1)})$, $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, and $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q1)})$ the G test statistics are significant for $(y_{1t}, y_{2t}) = (y_t^{DAX\ 100}\ y_t^{USB})$ suggesting respectively that there exists Granger causality from U.S. two year bond yield (USGG2YR) to German stock market index (DAX 100) in mean, in left tails of the distributions and from left tail of the U.S. two year bond yield (USGG2YR) to right tail of the German stock market index (DAX 100). However, there exists significant Granger causality in many parts of distributions. One may conclude that DAX 100 index is dependent on USGG2YR.

On the other hand, there is not any causal relationship in the opposite direction. German stock market index (DAX 100) has not any influence on the U.S. two year bond yield (USGG2YR).

Table 3.22 : G test Statistics for U.S. bond yield and DAX 100.

			$(y_{1t}, y_{2t}) = (y_t^{DAX\ 100}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{DAX\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1	**99.67*** **	3.457	76.59***	0.515	0.98	4.32**	52.05***	1.876	2.094	0.033	0.826	0.055	0.213	1.741
		5	**110.5*** **	23.91***	84.07***	3.732	3.746	12.48**	64.5***	5.771	5.518	8.036	2.727	2.646	3.033	3.359
		10	**112.9*** **	25.86***	85.171	9.113	17.349	16.516	75.32***	7.581	13.418	12.100	12.112	7.132	4.197	7.516
	$\Theta_{2t}^{(2)}$	1	1.252	**4.51*** **	4.44**	3.497	0.723	0.01	0.392	0.437	1.208	1.930	1.252	2.253	0.088	0.197
		5	16.79***	7.477	12.94**	7.062	8.413	2.775	5.086	11.584	9.834	9.864	6.459	10.428	7.825	11.630
		10	19.09**	13.993	14.672	16.421	9.250	7.227	6.128	15.188	19.132	13.799	9.796	12.712	11.429	18.830
	$\Theta_{2t}^{(q1)}$	1	85.56***	8.66***	**63.44*** **	0.323	4.771	6.08***	**39.71*** **	2.427	0.464	0.001	4.447	0.244	0.136	1.224
		5	95.37***	13.25***	**73.51*** **	1.882	9.103	12.47***	**44.14*** **	4.212	5.467	1.025	6.072	4.331	6.086	2.984
		10	97.19***	16.415	**73.85*** **	5.175	21.842	16.097	**54.78*** **	6.679	9.295	4.228	18.681	5.511	6.267	6.578
	$\Theta_{2t}^{(q2)}$	1	2.317	4.06**	0.335	1.373	0.006	0.026	3.305	0.078	0.593	0.28	4.375	1.428	0.711	0.07
		5	6.699	11.06**	7.938	7.372	1.838	3.355	6.424	3.873	7.601	5.737	8.494	7.088	6.217	14.928
		10	10.223	12.329	12.566	14.047	6.900	16.827	7.654	10.867	8.873	12.002	16.627	11.155	16.123	16.231
	$\Theta_{2t}^{(q3)}$	1	3.505	1.442	7.27***	0.225	6.462	0.008	0.132	0.492	0.887	0.477	1.003	1.032	0.472	0.014
		5	5.080	3.656	10.62**	2.868	12.213	1.663	1.666	7.807	7.587	1.433	8.341	3.071	5.389	3.596
		10	9.706	12.814	16.160	10.588	12.608	12.303	7.188	17.935	12.350	4.220	13.320	6.406	12.491	7.852
	$\Theta_{2t}^{(q4)}$	1	16.41***	0.5	14.02***	0.284	0.002	3.306	3.499	0.656	2.863	0.851	0.35	0.143	0.043	0.956
		5	19.17***	10.403	19.18***	0.976	0.394	11.06**	5.848	1.467	6.590	1.711	2.282	2.142	1.859	1.597
		10	25.29***	21.08**	24.21***	3.860	4.843	14.367	11.175	13.113	17.489	9.236	3.699	5.533	13.082	11.348
	$\Theta_{2t}^{(q5)}$	1	37.25***	0	24.02***	0.679	0.246	0.243	**20.69*** **	0.009	2.844	1.044	0.32	1.334	0.702	0.148
		5	46.66***	12.13**	30.94***	3.637	7.316	4.377	**34.94*** **	10.684	4.245	12.77**	3.401	7.844	6.354	5.322
		10	47.64***	17.79**	32.82***	7.987	14.317	8.073	**42.02*** **	15.607	23.468	23.1***	6.400	11.955	10.776	9.783

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

Table 3.23 shows that there is a strong relationship between London stock market index (FTSE 100) and U.S. two year bond yield (USGG2YR). From table it can be seen that at all parts of the distribution there exists strong causal relationship from U.S. two year bond yield (USGG2YR) to the London stock market index (FTSE 100). The evidence shows that the London stock market index (FTSE 100) is dependent on the U.S. two year bond yield (USGG2YR).

In other respects, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$ the G test statistic with n=1 is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{FTSE\ 100})$ suggesting that left tail of the London stock market index (FTSE 100) might weakly Granger cause left tail of the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when London stock index FTSE 100 is falling, U.S. two year bond yield (USGG2YR) is affected negatively. On the other side, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q5)})$ the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{FTSE\ 100})$ suggesting that right tail of the London stock market index (FTSE 100) could Granger cause right tail of the U.S. two year bond yield (USGG2YR). Hence, we may conclude that during bull market, when London stock index FTSE 100 is rising, U.S. two year bond yield (USGG2YR) is affected positively.

Table 3.23 : G test Statistics for U.S. bond yield and FTSE 100.

			$(y_{1t}, y_{2t}) = (y_t^{FTSE\ 100}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{FTSE\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1	104.9***	8.3***	77.2***	1.107	1.334	1.547	68.2***	0.352	6.5***	2.509	1.032	1.708	1.285	2.572
		5	131.9***	28.5***	104.2***	3.268	16.3***	12.9**	83.8***	1.496	11.1**	5.901	3.199	5.577	4.384	3.115
		10	134.2***	32.9***	107.8***	6.494	20.8**	23.0***	84.7***	7.825	17.310	10.622	10.156	10.791	8.840	11.205
	$\Theta_{2t}^{(2)}$	1	5.05**	10.1***	14.3***	0.633	17.8***	6.7***	1.051	0.007	0.185	0.697	0.925	0.001	0.054	0.131
		5	12.52**	16.7***	24.***	2.361	23.5***	7.099	2.655	5.571	9.894	5.455	10.379	5.152	4.768	7.970
		10	19.13**	30.6***	29.2***	2.783	33.1***	14.879	6.169	12.007	14.478	8.690	13.759	7.640	6.167	16.433
	$\Theta_{2t}^{(q1)}$	1	103.7***	18.6***	70.1***	1.247	7.2***	2.747	52.4***	0.123	1.536	**4.6****	2.723	1.134	0.011	0.027
		5	123.5***	31.2***	86.9***	9.706	16.7***	11.9**	59.2***	1.148	14.1***	9.466	4.947	5.373	1.763	0.64
		10	125.6***	39.2***	87.6***	15.492	21.3***	18.**	63.8***	8.264	23.0***	17.323	11.847	10.386	3.488	7.396
	$\Theta_{2t}^{(q2)}$	1	0.044	8.4***	0.304	0.975	0.508	0.002	1.509	0.426	0	0.002	0.749	0.493	2.382	0.034
		5	3.085	12.8**	3.121	5.239	8.504	1.862	3.552	3.491	8.084	1.591	4.294	2.823	5.443	3.193
		10	5.556	14.812	6.918	8.058	9.547	5.800	6.595	7.894	10.145	7.938	6.079	5.889	16.850	7.851
	$\Theta_{2t}^{(q3)}$	1	0.282	6.7***	3.055	0.225	6.1***	5.6***	9.0***	0.701	0.001	0.871	0.944	0.53	0.037	0.679
		5	0.974	7.823	4.067	1.914	8.838	8.553	9.910	11.276	7.058	3.341	9.747	7.126	1.425	17.6***
		10	6.533	16.100	11.710	7.947	21.331	9.919	16.360	14.729	10.320	10.618	11.688	13.122	17.352	19.7**
	$\Theta_{2t}^{(q4)}$	1	19.7***	0.789	19.3***	0.089	0.982	0.166	11.4***	4.291	1.819	2.763	0.395	0.149	1.044	2.471
		5	21.4***	16.556	26.7***	1.876	2.003	13.9***	16.6***	7.288	7.872	8.133	0.882	1.303	3.737	6.084
		10	29.5***	21.470	39.7***	11.092	6.079	23.***	23.5***	10.991	8.662	18.234	11.528	2.410	8.410	8.257
	$\Theta_{2t}^{(q5)}$	1	45.6***	0.439	15.7***	2.020	2.391	0.183	39.3***	4.1**	12.3***	0.037	0.111	1.917	0.295	**6.1*****
		5	59.4***	5.798	20.5***	8.760	11.092	2.986	48.2***	10.9**	13.8***	3.391	2.955	5.090	6.167	**12.3****
		10	61.3***	13.959	24.***	9.442	17.448	16.397	52.8***	13	18.1**	4.085	6.784	8.589	7.714	**18.5****

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

Table 3.24 shows that there is a strong relationship between U.S. stock market index (S&P 500) and U.S. two year bond yield (USGG2YR). From table it can be seen that at all parts of the distribution there exists strong causal relationship from U.S. two year bond yield (USGG2YR) to the U.S. stock market index (S&P 500). The evidence shows that the U.S. stock market index (S&P 500) is dependent on the U.S. two year bond yield (USGG2YR).

In other respects, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$ the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{S\&P\ 500})$ suggesting that left tail of the U.S. stock market index (S&P 500) might Granger cause left tail of the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when the U.S. stock market index (S&P 500) is falling, U.S. two year bond yield (USGG2YR) is affected negatively.

Table 3.24 : G test Statistics for U.S. bond yield and S&P 500.

	Φ_{2t}	n	$\Phi_{1t}=$	$(y_{1t}, y_{2t}) = (y_t^{S\&P500}, y_t^{USB})$ $\Phi_{1t}^{(1)}$	$\Phi_{1t}^{(2)}$	$\Phi_{1t}^{(q1)}$	$\Phi_{1t}^{(q2)}$	$\Phi_{1t}^{(q3)}$	$\Phi_{1t}^{(q4)}$	$\Phi_{1t}^{(q5)}$	$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{S\&P500})$ $\Phi_{1t}^{(1)}$	$\Phi_{1t}^{(2)}$	$\Phi_{1t}^{(q1)}$	$\Phi_{1t}^{(q2)}$	$\Phi_{1t}^{(q3)}$	$\Phi_{1t}^{(q4)}$	$\Phi_{1t}^{(q5)}$
Granger causality in moments	$\Phi_{2t}^{(1)}$	1		115.7***	17.03***	114.9***	7.43***	9.41***	16.63***	47.02***	0.276	1.646	0.598	0.002	0.355	1.803	0.053
		5		120.4***	30.22***	124.9***	8.994	17.97***	24.97***	53.04***	2.742	6.707	9.924	3.154	8.876	6.031	2.062
		10		127.7***	32.98***	130.63***	16.233	26.49***	28.96***	57.23***	5.559	16.048	12.802	8.994	10.024	9.346	9.106
	$\Phi_{2t}^{(2)}$	1		6.53***	6.9***	18.6***	3.810	9.09***	6.3***	2.477	0.296	0.016	0.045	0.089	3.392	2.684	0.104
		5		9.8*	9.77*	21.44***	9.001	21.66***	7.194	7.598	0.932	8.361	4.519	7.317	8.479	6.686	1.234
		10		21.2***	15.25	26.97***	15.675	24.7***	9.475	13.587	7.065	12.600	9.680	13.176	15.710	8.705	8.837
	$\Phi_{2t}^{(q1)}$	1		116.7***	56.02***	116***	2.021	32.3***	23.94***	17.09***	0.663	1.283	**4.45*** **	2.008	1.531	6.24***	0.01
		5		125.1***	61.16***	121.1***	4.636	36.6***	26.09***	26.62***	1.961	9.480	**12.86*** **	6.826	11.842	8.060	1.657
		10		130.1***	68.54***	127.7***	13.373	46.2***	29.6***	31.7***	4.818	18.888	15.192	13.047	14.670	12.965	5.711
	$\Phi_{2t}^{(q2)}$	1		0.106	14.1***	0.185	0.916	0.057	6.52***	8.96***	0.245	0.001	1.968	0.881	0.124	1.014	0.025
		5		5.370	15.37***	6.604	5.122	3.669	11.35**	22.28***	2.409	4.408	6.864	6.113	1.452	5.093	1.751
		10		7.172	19.9***	11.2	6.785	17.610	15.989	26.82***	3.668	5.732	11.876	7.631	3.285	17.762	5.647
	$\Phi_{2t}^{(q3)}$	1		0.656	31.71***	12.99***	0.689	29.7***	2.695	4.87***	1.553	0.039	0.642	0.683	1.493	0.063	0.514
		5		3.436	34.81***	14.33***	5.653	31.11***	7.659	10.607	4.940	10.272	7.685	9.876	7.237	2.509	1.917
		10		6.487	41.92***	20.14**	7.677	38.55***	7.772	11.119	5.591	10.217	10.081	11.627	12.221	7.155	5.313
	$\Phi_{2t}^{(q4)}$	1		21.29***	27***	18.47***	0.052	0.435	1.532	4.226	7.84***	1.025	5.55***	0.282	2.267	4.694	1.075
		5		23.3***	31.5***	19.82***	2.133	5.914	6.282	10.573	16.49***	8.471	8.212	0.882	6.589	5.180	7.405
		10		26.5***	35.02***	23.4***	7.139	6.717	12.533	12.745	20.22**	11.803	12.750	6.629	9.166	10.836	7.949
	$\Phi_{2t}^{(q5)}$	1		83.5***	1.755	32.9***	9.94***	0.833	4.814	36.3***	0.999	0.342	0.2	0.854	2.753	1.155	0.059
		5		85.7***	9	39.8***	12.46**	4.176	9.166	42.07***	6.572	7.043	12.478	2.955	7.163	4.956	2.354
		10		86.1***	11.29	40.57***	15.313	14.353	12.100	43.4***	7.312	13.606	15.642	8.204	11.199	6.407	4.413

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

To sum up, as can be seen from Table 3.25, it may be clarified that there exists contagion from the U.S. bond market to the Japan stock market. The evidence shows that the London stock market index (FTSE 100), German stock market index (DAX 100) and U.S. stock market index (S&P 500) are dependent on the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when London stock index FTSE 100 is falling, U.S. two year bond yield (USGG2YR) is (weakly) negatively affected. Moreover, during bull market, when London stock index FTSE 100 is rising, U.S. two year bond yield (USGG2YR) is affected positively.

Table 3.25 : Summary of Granger causality test result between U.S. bond market and developed stock markets.

	Direction of causality	
Negative contagion	USGG2YR→NIKKEI225	
Strong dependence	USGG2YR→DAX 100	
Strong dependence	USGG2YR→FTSE 100	
Strong dependence	USGG2YR→S&P 500	
Positive contagion		FTSE 100→USGG2YR
Negative contagion		FTSE 100→USGG2YR (weakly)
Negative contagion		S&P 500→USGG2YR

3.5.5 Granger causality tests in moments between U.S. two year bond yield and emerging stock market indices

In this part of the study, Granger causality tests in moments are carried out between U.S. two year bond yield and emerging stock market indices.

By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q1)})$, the results in Table 3.26 shows that the G test statistic with n = 1 is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{BIST\ 100})$ suggesting that the left tail of the Turkish stock market index (BIST 100) distribution, could weakly Granger cause the right tail of U.S. two year bond yield (USGG2YR).

However, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}\ y_t^{USB})$ suggesting that the left tail of U.S. two year bond yield (USGG2YR) distribution could Granger cause the right tail of the Turkish stock (BIST 100) distribution.

Further, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}\ y_t^{USB})$ suggesting that the left tail of U.S. two year bond yield

(USGG2YR) distribution could Granger cause the left tail of the Turkish stock (BIST 100) distribution. This result indicate that there exist financial contagion from U.S. bond market to Turkish stock market during falling market periods.

However, by setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q3)}$, $\Theta_{2t}^{(q3)}$), the G test statistic is significant for (y_{1t}, y_{2t}) = ($y_t^{BIST\ 100}$ y_t^{USB}) suggesting that the center of U.S. two year bond yield (USGG2YR) distribution could Granger cause the center of Turkish stock market (BIST 100) distribution.

Therefore, one may conclude that BIST 100 is dependent on USGG2YR by the reason of significant Granger causality in the center of the distributions.

Table 3.26 : G test Statistics for U.S. bond yield and BIST 100.

				$(y_{1t}, y_{2t}) = (y_t^{BIST\ 100}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{BIST\ 100})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**14.4*****	0.806	4.14**	0.007	2.876	0.113	11.6***	0.097	5.004	2.920	0.297	8.11***	1.176	1.446
		5		**19.3*****	4.315	11.05**	3.063	6.118	4.952	14.7***	1.269	6.794	3.183	0.974	12.4**	3.111	6.055
		10		**24.3*****	6.679	17	9.985	7.990	5.885	18.2***	3.928	10.162	6.636	5.252	16.860	5.984	9.075
	$\Theta_{2t}^{(2)}$	1		6.16***	0.318	4.39**	0.263	0.002	7.87***	0.266	0.157	0.169	0.004	0.593	0	1.011	0.189
		5		9.788	4.588	5.728	1.842	0.523	8.971	2.122	3.551	13.870	1.994	3.725	2.164	7.361	2.178
		10		20.1**	19.048	21.6***	20.031	4.483	11.316	19.669	9.680	19.819	9.661	8.126	8.143	13.463	3.205
	$\Theta_{2t}^{(q1)}$	1		27.3***	0.004	**11.56*****	1.802	0.08	0.723	**18.7*****	1.582	2.296	0.002	0.359	8.4***	0.222	**4.57****
		5		31.4***	3.946	**15.97*****	6.211	4.509	2.658	**21.8*****	3.042	4.604	1.790	1.425	9.614	3.922	6.962
		10		34.8***	9.522	**20.2****	13.107	8.785	3.866	**30.08*****	10.724	11.371	12.403	5.461	12.259	6.752	10.828
	$\Theta_{2t}^{(q2)}$	1		0.094	4.605	1.110	0.504	0.241	3.706	0.112	0.095	0.008	0.633	0.199	7.78***	2.767	0.7
		5		5.977	9.342	5.597	1.406	2.362	6.902	6.504	6.225	3.733	10.298	4.225	12.13**	6.372	5.918
		10		10.661	11.321	11.103	8.465	3.249	10.014	8.480	16.657	8.084	15.187	9.324	18.5***	10.629	7.385
	$\Theta_{2t}^{(q3)}$	1		2.588	1.257	2.527	0.107	**7.81*****	3.137	0.276	1.463	0.017	2.422	0.768	1.042	0.642	0.5
		5		6.905	5.373	7.042	1.545	**16.5*****	11.876	4.830	3.304	5.487	6.282	4.881	1.386	1.045	2.207
		10		11.404	14.750	14.892	4.141	**29.47*****	15.378	11.019	7.097	13.140	8.754	8.115	6.561	2.404	7.035
	$\Theta_{2t}^{(q4)}$	1		1.419	1.587	0.226	0.299	0.341	1.044	0.294	0.504	2.705	0.015	1.043	0	0.088	1.148
		5		4.807	2.843	1.625	6.980	2.214	7.516	7.626	4.460	4.187	1.029	5.662	4.958	6.575	4.326
		10		8.928	6.419	8.886	13.733	5.465	12.865	13.293	5.238	8.796	2.550	8.812	6.995	12.502	9.221
	$\Theta_{2t}^{(q5)}$	1		6.78***	0.683	0.959	0.002	4.058	0.102	**8.09*****	0.422	0.886	0.475	1.198	0.898	0.715	0.008
		5		13.5***	3.215	9.987	1.461	10.205	8.700	**12****	7.252	5.525	2.938	2.462	11.743	4.502	8.229
		10		15.428	7.422	18.058	4.201	20.126	14.349	15.798	12.260	8.435	4.627	3.642	15.822	7.306	10.363

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

We can observe from the significance of the test statistics that U.S. two year bond yield (USGG2YR) may Granger cause the Indonesian stock index (IDX) in mean. By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic is significant for $(y_{1t}, y_{2t}) = (y_t^{IDX}\ y_t^{USB})$ suggesting that the left tail of U.S. two year bond yield (USGG2YR) distribution could Granger cause the left tail of the Indonesian stock index (IDX) distribution. According to Table 3.27, we find evidence of contagion in falling stock market periods and regards U.S. two year bond yield (USGG2YR) as a driver of spillover. An extreme downside risk from U.S. bond market has a predictive content for an extreme downside risk for Indonesian stock market. On the other hand, there is not any causal relationship in opposite direction. Indonesian stock index (IDX) has no effect on the U.S. two year bond yield (USGG2YR).

Table 3.27 : G test Statistics for U.S. bond yield and IDX.

Granger causality in moments			$(y_{1t}, y_{2t}) = (y_t^{IDX}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{IDX})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
	$\Theta_{2t}^{(1)}$	1	8.8***	0.793	10.4***	0.05	0.258	0.496	4.6**	0.004	1.251	3.302	3.454	1.084	1.616	3.597
		5	15.8***	12.911	17.9***	1.857	7.298	4.981	8.764	6.786	3.670	7.903	6.902	5.694	5.554	11.087
		10	21.5***	12.630	27.5***	9.426	21.429	9.822	12.791	18.284	10.684	14.090	12.230	10.699	14.958	20.675
	$\Theta_{2t}^{(2)}$	1	0.68	0.805	1.346	1.339	12.3***	0.003	0.047	1.038	1.869	2.813	5.696	0.187	0.064	0.028
		5	3.577	8.145	9.230	6.724	17.5***	4.549	1.069	2.894	7.085	3.832	7.154	2.744	11.953	3.734
		10	9.281	13.524	12.595	14.191	17.3**	6.886	9.642	17.319	15.110	11.813	11.204	8.583	16.813	16.881
	$\Theta_{2t}^{(q1)}$	1	7.6***	1.300	12.4***	0.04	1.804	0.211	3.938	0.003	0.679	1.930	1.499	0	3.247	1.619
		5	19.3***	12.143	34.8***	5.017	8.093	5.253	5.888	4.526	4.205	3.445	1.908	2.600	4.761	6.194
		10	22.8***	15.924	40.5***	11.550	16.495	9.120	11.584	10.964	10.450	5.701	9.589	5.009	12.754	9.916
	$\Theta_{2t}^{(q2)}$	1	0.11	0.207	0.584	0.043	0.004	0	0.623	0.187	0.279	0.384	0.205	1.614	0.039	0.605
		5	0.608	6.720	5.818	9.969	4.203	0.58	3.937	1.446	1.577	2.664	4.902	3.996	1.880	2.266
		10	6.372	8.159	12.765	16.426	7.270	5.967	4.339	4.375	4.639	6.411	9.668	7.485	7.707	8.187
	$\Theta_{2t}^{(q3)}$	1	0.523	4.906	0.606	0.128	1.871	0.124	0.001	0.603	0.849	1.521	0.078	0.54	0.359	0.768
		5	5.634	6.352	7.837	8.927	3.603	12.124	0.375	7.300	14.811	8.969	8.516	10.546	3.289	9.779
		10	8.558	11.559	12.049	11.395	6.321	13.773	4.216	10.020	15.800	14.721	14.255	11.622	7.375	12.378
	$\Theta_{2t}^{(q4)}$	1	0	0.74	0.038	0.181	0.675	0.033	0.722	0.56	0.236	3.095	0.39	2.191	0.004	0.086
		5	4.759	4.717	10.034	3.190	4.045	4.032	2.169	1.277	3.725	3.990	3.968	6.890	2.358	4.065
		10	6.564	11.331	16.323	4.200	13.553	13.256	4.056	5.815	13.819	5.899	6.240	12.050	11.313	9.117
	$\Theta_{2t}^{(q5)}$	1	3.7***	0.577	4.9**	0.004	0.73	0.881	3.615	0.247	1.255	2.487	1.358	0.164	0.779	0.639
		5	10.9***	8.716	10.9**	0.42	4.315	4.950	6.219	0.595	4.689	3.817	8.887	4.099	6.090	1.565
		10	13.299	16.462	15.967	13.550	10.779	10.579	10.558	2.562	16.673	11.100	15.584	7.975	8.356	6.941

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

According to Table 3.28 we find weak evidence of Granger causality in both directions. By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(2)}, \Theta_{2t}^{(q1)})$, the G test statistic n=1 is significant for $(y_{1t}, y_{2t}) = (y_t^{KLCI}\ y_t^{USB})$ suggesting that the left tail of two year bond yield (USGG2YR) distribution could weakly Granger cause the variance of the Malaysian stock index (KLCI) distribution. We may conclude that when U.S. bond market is falling, Malaysian stock market may experience turbulence. However, By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(2)})$, the G test statistic with $n = 1$ is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{KLCI})$ suggesting that the variance of the Malaysian stock index (KLCI) distribution, could weakly Granger cause the right tail of two year bond yield (USGG2YR). Therefore, one may suggest that KLCI is a good diversification alternative for investors investing in USGG2YR.

Table 3.28 : G test Statistics for U.S. bond yield and KLCI.

				$(y_{1t}, y_{2t}) = (y_t^{KLCI}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{KLCI})$						
	Θ_{2t}	n	Θ_{1t}=	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		0.128	2.177	1.684	1.939	0.79	1.996	0.055	1.363	2.059	0.192	0.659	0.024	1.107	0.464
		5		1.333	6.922	4.554	8.454	3.909	3.222	1.051	3.106	6.912	2.069	1.015	2.857	3.655	3.936
		10		4.765	18.290	12.909	10.821	7.147	9.051	4.259	8.329	11.068	10.315	4.850	7.143	7.103	8.035
	$\Theta_{2t}^{(2)}$	1		0.009	0.799	0.011	0.065	0.001	0.001	0.007	2.207	2.315	0.121	0.078	5.568	0.426	**5.0****
		5		1.918	12.922	1.143	1.743	5.301	10.560	2.989	6.581	9.938	1.728	1.922	10.887	13.284	9.431
		10		10.196	15.894	12.794	7.666	11.300	21.181	6.154	13.139	21.560	3.303	4.742	13.909	22.384	16.837
	$\Theta_{2t}^{(q1)}$	1		0.003	**3.8****	3.334	2.486	0.288	0.117	0.053	0.958	0.012	0.488	1.028	0.036	1.907	1.115
		5		3.361	9.551	6.427	5.609	3.487	4.881	3.097	5.458	2.800	3.468	2.622	1.045	7.949	8.703
		10		6.357	14.639	11.595	8.534	7.877	12.685	4.496	10.839	4.169	5.792	7.749	7.066	18.968	12.920
	$\Theta_{2t}^{(q2)}$	1		1.751	0.032	0.001	0.98	0.036	0.04	0.837	0.09	0.935	0.149	0.557	2.020	0.792	0.603
		5		3.109	3.065	3.220	2.475	6.455	5.324	4.069	1.613	14.938	4.168	5.349	5.683	6.644	5.388
		10		6.532	11.401	8.102	6.910	13.544	10.113	10.035	10.889	16.308	8.540	20.266	8.983	16.772	7.761
	$\Theta_{2t}^{(q3)}$	1		0.786	0.044	1.313	0	0.162	0.174	1.455	2.195	0.043	1.823	0.089	0.745	0.079	5.3**
		5		5.699	5.220	3.927	0.999	2.355	9.124	18.121	6.979	7.032	6.023	3.663	3.100	6.597	12.0**
		10		7.532	8.256	8.479	4.240	3.733	10.408	19.031	9.678	9.423	9.346	9.732	4.540	11.560	17.354
	$\Theta_{2t}^{(q4)}$	1		0.012	1.020	0.176	0.495	0.262	0.019	0.151	0.58	2.666	2.382	0.267	1.924	1.048	0.289
		5		2.684	7.957	3.727	2.034	1.329	6.959	9.272	6.366	5.616	8.274	2.191	3.291	4.861	2.790
		10		5.020	14.711	7.866	7.842	4.399	13.765	14.011	8.200	9.187	9.765	3.475	8.556	6.018	7.545
	$\Theta_{2t}^{(q5)}$	1		0.074	0.029	0.927	0.007	2.627	0.613	0.009	0.121	0.183	0.05	1.231	0.646	2.480	0.005
		5		1.310	2.034	2.701	3.050	7.125	2.464	0.791	10.716	2.652	5.010	3.613	9.109	9.072	8.167
		10		9.575	9.540	13.939	7.606	9.046	10.675	5.161	18.403	5.410	17.701	4.735	12.333	12.611	12.295

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.29 we might conclude that there is a strong relationship between Indian stock index (SENSEX) and U.S. two year bond yield (USGG2YR). By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(1)}, \Theta_{2t}^{(1)})$, $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, and $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q1)})$ the G test statistics are significant for $(y_{1t}, y_{2t}) = (y_t^{SENSEX}\ y_t^{USB})$ suggesting respectively that there exists Granger causality from U.S. two year bond yield (USGG2YR) to Indian stock index (SENSEX) in mean, in left tails of the distributions and from left tail of U.S. two year bond yield (USGG2YR) to the right tail of Indian stock index (SENSEX). In conclusion, it can be seen that among most parts of the distribution there exists strong causal relationship from U.S. two year bond yield (USGG2YR) to Indian stock index (SENSEX). We find evidence that Indian stock index (SENSEX) is affected by the U.S. two year bond yield (USGG2YR). In other respects, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$ the G test statistic with n=1 is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{SENSEX})$ suggesting that left tail of the Indian stock index (SENSEX) might weakly Granger cause left tail of the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when Indian stock index (SENSEX) is falling, U.S. two year bond yield (USGG2YR) may be affected negatively.

Table 3.29 : G test Statistics for U.S. bond yield and SENSEX.

				$(y_{1t}, y_{2t}) = (y_t^{SENSEX}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{SENSEX})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**20.8*** **	0.053	20.6***	0.61	2.504	0.811	9.3***	2.945	2.462	6.9***	1.497	1.160	0.104	0.228
		5		**28*** **	1.993	28.3***	2.262	10.896	10.403	19.2***	5.330	4.845	9.187	2.356	3.809	1.745	1.435
		10		**35.1*** **	4.232	34.0***	4.038	11.528	13.734	29.4***	13.992	9.827	11.163	4.582	8.740	5.975	9.391
	$\Theta_{2t}^{(2)}$	1		4.7**	0.404	1.986	1.163	2.446	0.129	0.964	0.885	1.098	3.430	4.477	1.287	0.582	0.014
		5		13.1**	6.266	8.812	3.259	2.639	2.245	7.594	7.385	7.184	8.758	8.067	11.385	5.084	8.309
		10		15.625	11.461	8.430	5.559	4.314	8.911	11.592	11.724	12.095	14.184	12.787	13.583	10.017	14.436
	$\Theta_{2t}^{(q1)}$	1		21.9***	2.684	**20.7*** **	0.753	7***	0.652	**6*** **	2.301	0.937	**4.4** **	0.201	0.651	0.287	0.28
		5		29.1***	7.750	**31*** **	1.520	11.7**	10.604	**13.7*** **	8.484	2.982	8.635	1.314	8.101	11.368	1.227
		10		34.2***	9.900	34.596	3.714	12.365	14.521	**21.8*** **	16.045	8.716	15.510	4.904	19.375	14.412	5.542
	$\Theta_{2t}^{(q2)}$	1		0.047	1.041	0.34	1.084	0.649	0.093	0.485	0.097	0.24	1.893	0.024	0.535	0.263	0.092
		5		2.379	5.270	2.980	2.695	1.473	2.764	1.053	3.308	0.867	4.938	5.244	3.722	3.163	3.514
		10		5.769	6.831	5.357	8.194	3.989	8.109	3.181	11.527	10.348	10.824	7.076	11.234	5.097	10.935
	$\Theta_{2t}^{(q3)}$	1		0.007	3.631	0.17	0.027	0.826	0.004	0.306	0.001	0.929	1.921	0.142	2.039	0.079	0.252
		5		2.419	4.742	8.252	1.676	6.558	2.942	1.272	8.979	11.907	3.683	2.282	8.482	3.187	12.401
		10		5.587	7.398	10.875	7.438	8.267	8.991	3.823	11.522	12.939	4.880	6.487	16.208	9.642	16.087
	$\Theta_{2t}^{(q4)}$	1		10.4***	0.663	6.6***	0.543	0.002	0.006	2.888	0.017	1.542	0.02	0.725	0.283	0.083	0.914
		5		14.7***	4.326	9.802	3.237	2.501	4.276	4.149	1.057	1.771	2.526	4.309	1.326	2.287	2.331
		10		18.8**	8.042	12.378	3.786	5.286	8.133	8.375	5.506	4.227	6.645	4.956	2.429	4.587	6.916
	$\Theta_{2t}^{(q5)}$	1		4.428	0.498	8.9***	0.583	0.835	0.393	3.5**	1.878	0.802	4.6**	0.022	0.832	0.307	0.327
		5		8.875	3.881	15***	3.387	3.399	7.116	9.873	8.546	3.567	8.601	2.634	1.785	2.105	5.007
		10		15.640	9.395	20.5**	7.075	4.823	12.702	19.4**	15.935	10.965	13.321	4.741	3.191	8.327	9.619

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As can be seen from Table 3.30, we might conclude that there is a strong relationship between Mexican stock market index (IPC) and U.S. two year bond yield (USGG2YR). Especially, there exists Granger causality among almost all parts of the distribution from U.S. two year bond yield (USGG2YR) to the Mexican stock market index (IPC). In this case, we could not suggest that there is flight to quality or contagion effect although Granger causality might be seen between the tails of these two distributions. It can be observed that the Mexican stock market index (IPC) is dependent on the U.S. two year bond yield (USGG2YR). However, there is no causal relationship in opposite direction. Mexican stock market index (IPC) has no effect on the U.S. two year bond yield (USGG2YR).

Table 3.30 : G test Statistics for U.S. bond yield and IPC.

Granger causality in moments

			$(y_{1t}, y_{2t}) = (y_t^{IPC}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{IPC})$						
Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
$\Theta_{2t}^{(1)}$	1		65.0***	6.4***	70.1***	2.202	0.892	10.5***	34.7***	0.019	3.063	1.106	0.474	0.271	5.037	1.512
	5		73.9***	7.885	79.3***	6.647	3.104	12.0**	40.5***	3.872	5.699	5.302	2.017	2.826	6.461	2.440
	10		84.5***	15.551	88.6***	14.639	8.278	18.3**	45.4***	5.904	14.142	8.346	7.640	5.408	9.478	5.899
$\Theta_{2t}^{(2)}$	1		2.965	4.4**	10.5***	5.8***	7.192	1.133	1.393	0.075	0.07	0.031	0.407	0.928	0.476	0.195
	5		6.442	6.196	15.1***	10.9**	9.287	9.609	1.792	3.184	2.328	3.204	6.150	3.512	2.569	1.078
	10		13.818	8.522	22.1***	22.0***	12.386	9.230	10.0***	8.005	4.145	9.413	11.806	9.267	3.509	5.625
$\Theta_{2t}^{(q1)}$	1		67.4***	16.4***	67.2***	0.71	3.933	11.3***	27.9***	0	0.758	0.947	0.893	0.022	1.878	0.923
	5		78.5***	17.5***	76.4***	1.427	9.342	13.9***	33.9***	3.282	5.436	2.236	4.155	4.840	2.448	7.252
	10		82.1***	20.5**	79.7***	5.150	10.979	17.390	37.6***	12.473	12.782	8.797	12.260	6.237	8.045	14.355
$\Theta_{2t}^{(q2)}$	1		0.406	2.894	4.5**	0.36	0.172	1.314	0.004	0.791	0.516	0.054	0.226	0.359	0.056	1.163
	5		3.168	6.204	12.1**	14.7***	3.002	2.846	2.501	5.787	1.946	1.867	2.362	10.322	3.601	9.750
	10		8.068	7.702	20.3**	16.926	7.727	5.345	6.391	19.014	9.102	16.018	3.487	13.414	5.676	15.540
$\Theta_{2t}^{(q3)}$	1		0.593	15.3***	1.068	1.470	7.293	0.217	6.206	0.943	1.643	0.454	4.409	0.05	0.496	2.610
	5		1.803	22.9***	7.531	7.495	8.278	2.358	8.392	5.518	6.463	2.742	6.832	0.462	3.313	2.818
	10		5.851	24.5***	9.611	8.685	10.806	6.959	11.916	11.088	20.865	10.595	15.022	13.099	3.823	14.510
$\Theta_{2t}^{(q4)}$	1		11.1***	1.024	7.1***	0.874	0.137	2.520	3.915	0.036	8.6***	1.578	4.989	0.31	0.033	0.433
	5		11.8**	8.845	7.703	6.603	4.648	6.787	6.722	4.885	14.5***	5.326	7.676	2.829	2.938	2.896
	10		17.571	12.486	12.194	16.897	10.925	11.175	10.006	7.157	15.442	8.003	17.052	7.532	7.430	11.717
$\Theta_{2t}^{(q5)}$	1		39.9***	0.248	19.1***	3.386	0.731	0.96	24.4***	0.001	1.192	0.458	0.042	0.16	3.606	0.912
	5		47.8***	2.114	30.1***	12.159	2.996	2.079	29.3***	2.113	2.750	3.005	1.578	5.418	4.991	3.076
	10		47.4***	8.120	30.8***	16.541	4.562	11.264	31.5***	3.970	9.632	5.636	7.793	8.880	9.981	6.099

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

We can observe from the significance of the test statistics that there is a strong relationship between Chile stock market index (IPSA) and U.S. two year bond yield (USGG2YR). As can be seen from Table 3.31 there exists Granger causality among almost all parts of the distribution from U.S. two year bond yield (USGG2YR) to the Chile stock market index (IPSA). It can be observed that Chile stock market index (IPSA) is highly affected by the U.S. two year bond yield (USGG2YR). However, there is no causal relationship in opposite direction. Hence, Chile stock market index (IPSA) has not any influence on the U.S. two year bond yield (USGG2YR).

Table 3.31 : G test Statistics for U.S. bond yield and IPSA.

				$(y_{1t}, y_{2t}) = (y_t^{IPSA}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{IPSA})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		37.0***	4.787	33.7***	0.784	0.223	8.3***	15.0***	0.413	3.376	1.185	2.143	0.431	0.938	3.432
		5		44.7***	7.634	36.0***	2.444	2.838	12.0**	22.6***	8.845	6.746	8.359	3.881	7.972	4.145	8.016
		10		52.7***	8.951	41.0***	7.453	4.757	13.925	27.8***	10.137	10.259	9.848	10.212	11.115	11.671	11.753
	$\Theta_{2t}^{(2)}$	1		6.7***	6.3***	14.5***	0.551	12.3***	7.3***	1.205	3.689	0.522	0.799	0.436	0.081	0.832	2.078
		5		9.841	6.520	19.6***	8.209	13.7***	11.3**	2.827	4.924	4.125	3.337	13.015	2.932	9.036	3.519
		10		11.489	7.425	23.8***	11.208	15.523	15.472	6.383	11.130	7.666	8.778	18.806	10.034	19.590	10.001
	$\Theta_{2t}^{(q1)}$	1		32.4***	6.8***	37.4***	0.165	2.436	6.6***	5.6***	0.053	0.511	0.198	0.214	0.685	1.929	0.18
		5		39.9***	8.628	43.3***	1.655	8.180	9.588	8.090	3.136	4.381	4.468	3.189	2.992	3.078	2.294
		10		41.8***	12.603	45.8***	10.217	11.719	13.319	11.121	5.315	9.194	5.674	11.158	12.752	18.485	7.481
	$\Theta_{2t}^{(q2)}$	1		0.008	0.29	0.113	0.925	0.221	0.113	0.6	0.819	0.001	0.009	0	0.937	0.313	0.229
		5		2.726	2.594	12.9***	3.218	7.260	2.055	5.949	6.610	2.976	1.640	1.789	3.639	5.707	13.150
		10		3.630	6.067	16.936	14.208	14.022	5.649	7.553	11.817	9.318	2.569	7.743	6.196	7.898	17.471
	$\Theta_{2t}^{(q3)}$	1		0.023	18.6***	3.130	2.147	5.3***	0.035	5.9***	0.005	1.714	1.044	0.226	1.071	0.719	1.251
		5		3.157	24.7***	8.255	8.512	14.9***	6.069	11.6***	1.961	2.587	4.409	1.755	6.199	10.134	6.845
		10		8.528	29.7***	14.596	11.404	21.4***	8.163	17.660	5.972	3.493	5.735	8.751	8.905	11.663	7.806
	$\Theta_{2t}^{(q4)}$	1		9.03***	0.973	6.7***	0.109	0.38	1.439	4.1**	0.758	0.393	0.253	0.456	0.051	0.305	0.373
		5		9.621	3.979	8.272	5.914	5.314	3.410	6.039	4.008	4.236	4.683	5.208	1.413	2.931	4.515
		10		14.468	8.705	12.894	10.859	11.177	13.388	12.027	11.995	13.444	10.220	11.921	9.827	15.953	8.910
	$\Theta_{2t}^{(q5)}$	1		12.5***	0.57	7.2***	2.943	0.452	2.114	9.8***	0.014	11.7***	3.483	2.139	0.755	1.128	2.163
		5		17.8***	1.309	9.613	6.575	3.376	5.682	14.9***	5.095	11.9**	8.534	8.257	9.123	7.443	6.452
		10		21.3***	6.864	15.773	16.598	10.628	7.655	18.3**	8.508	13.664	11.918	13.150	15.103	9.618	9.968

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

According to Table 3.32, there exists weak Granger causality from U.S. two year bond yield (USGG2YR) to the Argentina stock market index (MERVAL) in mean. In addition, by setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q1)}, \Theta_{2t}^{(q1)})$, the G test statistic with n=1 is significant for $(y_{1t}, y_{2t}) = (y_t^{MERVAL}\ y_t^{USB})$ suggesting that the left tail of U.S. two year bond yield (USGG2YR) distribution could weakly Granger cause the left tail of the Argentina stock index (MERVAL) distribution. We find weak evidence of contagion effect from U.S. bond market to Argentina stock market.

However, By setting $(\Theta_{1t}, \Theta_{2t}) = (\Theta_{1t}^{(q5)}, \Theta_{2t}^{(q1)})$, the G test statistic with $n = 1$ is significant for $(y_{1t}, y_{2t}) = (y_t^{USB}\ y_t^{MERVAL})$ suggesting that the left tail of the Argentina stock index (MERVAL) distribution, could weakly Granger cause the right tail of two year bond yield (USGG2YR). This phenomenon can be interpreted as a flight to quality effect from Argentina stock market to U.S. two year bond yield (USGG2YR) when Argentina is in falling periods. Hence, MERVAL may be a good diversification alternative for USGG2YR.

Table 3.32 : G test Statistics for U.S. bond yield and MERVAL.

			$(y_{1t}, y_{2t}) = (y_t^{MERVAL}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{MERVAL})$						
	Θ_{2t}	n	$\Theta_{1t}=$ $\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1	**5.6*** **	0.027	2.863	0.71	1.682	8.6***	1.094	2.973	0.514	4.4**	0.073	0.006	2.634	0.598
		5	8.567	1.799	6.269	4.076	7.144	11.2**	1.992	5.929	4.937	10.353	2.181	3.060	6.846	1.874
		10	11.092	7.655	14.547	7.857	10.835	13.362	6.192	8.047	5.257	12.762	17.217	9.009	23.144	3.434
	$\Theta_{2t}^{(2)}$	1	0.016	0.346	0.044	0.298	0.042	0.048	1.534	3.246	0.942	0.004	4.7**	5.842	1.163	2.224
		5	4.568	8.314	6.076	5.131	7.896	1.247	2.119	4.500	1.962	1.912	10.529	7.001	6.496	2.610
		10	14.475	10.459	9.926	11.206	16.840	4.053	6.638	6.209	4.572	8.520	18.7**	9.526	12.726	6.220
	$\Theta_{2t}^{(q1)}$	1	5.7***	0.819	**4.9** **	0.702	0.149	2.971	3.330	5.6***	0.209	2.157	0.072	1.144	0.411	**4.1** **
		5	7.958	5.455	6.030	4.132	2.523	4.125	3.912	8.263	3.382	8.818	5.368	2.484	3.114	6.678
		10	13.897	8.000	10.337	9.026	6.878	7.437	8.142	13.014	6.913	12.671	12.104	5.134	16.466	12.906
	$\Theta_{2t}^{(q2)}$	1	0.257	15.0***	2.013	0.992	0.034	0.175	0.047	0.916	0.128	0.18	0.844	0.769	2.250	0.798
		5	5.308	15.5***	3.330	6.257	2.895	3.368	3.770	1.671	4.994	1.769	4.560	8.172	5.539	4.540
		10	12.857	20.5**	10.989	8.162	4.232	4.060	7.459	11.865	9.852	8.145	16.667	15.554	8.564	13.252
	$\Theta_{2t}^{(q3)}$	1	0.31	2.664	0.005	0.882	1.088	1.904	0.694	2.523	0.434	0.103	0.015	6.2***	0.343	7.4***
		5	9.064	7.147	11.7**	3.553	5.816	5.828	2.232	5.774	8.554	1.626	1.929	8.361	1.228	13.1**
		10	12.372	12.371	15.439	6.464	13.891	11.281	10.191	6.324	18.772	10.047	9.802	11.591	3.706	16.773
	$\Theta_{2t}^{(q4)}$	1	0.079	0.812	0.102	0.002	0.25	1.074	0.481	0.348	2.470	0.682	0.719	2.642	7.4***	1.540
		5	2.731	4.612	9.593	5.072	6.597	3.411	3.565	7.135	5.386	2.125	6.297	4.447	11.0**	6.332
		10	4.975	8.747	14.894	10.218	17.050	4.834	4.806	7.664	8.276	3.160	14.254	8.500	12.287	11.002
	$\Theta_{2t}^{(q5)}$	1	1.596	0	0.596	0.844	3.022	10.7***	0.016	1.067	2.107	3.494	0.16	0.845	5.771	0.469
		5	11.6**	5.332	5.825	8.897	10.213	12.1***	1.742	7.304	11.108	7.812	2.933	8.694	6.242	6.603
		10	16.261	11.792	13.268	11.426	10.610	14.9***	11.339	16.530	13.110	13.364	19.604	12.759	12.214	11.086

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

Table 3.33 shows that there is a strong causal relationship between Brazilian stock index BOVESPA and U.S. two year bond yield (USGG2YR). Especially, there exists Granger causality among almost all parts of the distribution from U.S. two year bond yield (USGG2YR) to the Brazilian stock index (BOVESPA). In this case, we could not suggest that there is Flight to Quality effect although Granger causality might be seen between the tails of these two distributions. On the other hand, By setting (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(q1)}$, $\Theta_{2t}^{(2)}$), and (Θ_{1t}, Θ_{2t}) = ($\Theta_{1t}^{(1)}$, $\Theta_{2t}^{(2)}$), the G test statistics are significant for (y_{1t}, y_{2t}) = (y_t^{USB} $y_t^{BOVESPA}$) suggesting that the volatility in Brazilian stock index (BOVESPA) affects U.S. two year bond yield (USGG2YR). We may interpret this as Granger causality from variance of Brazilian stock index (BOVESPA) to the mean and left tail of U.S. two year bond yield (USGG2YR).

Table 3.33 : G test Statistics for U.S. bond yield and BOVESPA.

				$(y_{1t}, y_{2t}) = (y_t^{BOVESPA}, y_t^{USB})$							$(y_{1t}, y_{2t}) = (y_t^{USB}, y_t^{BOVESPA})$						
	Θ_{2t}	n	$\Theta_{1t}=$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$	$\Theta_{1t}^{(1)}$	$\Theta_{1t}^{(2)}$	$\Theta_{1t}^{(q1)}$	$\Theta_{1t}^{(q2)}$	$\Theta_{1t}^{(q3)}$	$\Theta_{1t}^{(q4)}$	$\Theta_{1t}^{(q5)}$
Granger causality in moments	$\Theta_{2t}^{(1)}$	1		**46.55*** **	3.54**	59.15***	0.849	8.6***	0.623	16.85***	0.057	2.508	0.139	1.202	0.015	2.420	0.021
		5		**51.67*** **	13.75***	65.02***	10.680	10.354	2.878	25.05***	0.686	6.983	1.050	5.457	1.871	8.053	1.483
		10		**58.11*** **	22.12***	67.37***	15.221	18.5**	7.649	29.48***	6.331	14.761	7.117	12.630	7.219	13.977	9.959
	$\Theta_{2t}^{(2)}$	1		5.86***	4.790	10.82***	3.261	2.733	1.241	0.137	3.86**	3.153	4.91**	1.331	0.822	0.168	1.629
		5		9.435	6.144	12.71**	13.62***	3.053	9.391	1.635	15.85***	4.473	15.16***	4.565	1.855	2.691	3.382
		10		14.186	16.504	14.932	23.9***	4.993	18.539	8.563	19.28**	8.900	24.45***	5.565	6.488	11.060	5.476
	$\Theta_{2t}^{(q1)}$	1		46.88***	14.47***	50.95***	0.296	15.62***	0.082	**14.2*** **	1.192	2.454	2.701	0.005	0.042	3.359	0.038
		5		50.3***	17.33***	53.67***	11.928	15.64***	3.365	**18.8*** **	3.388	5.453	4.008	4.131	2.758	7.671	0.98
		10		51.26***	28.06***	54.38***	13.695	23.9***	8.199	**22.10*** **	15.623	13.986	9.282	8.214	5.327	10.501	11.016
	$\Theta_{2t}^{(q2)}$	1		0.002	11.88***	0.003	0.285	1.073	0.161	0.006	4.609	0.896	4.246	0.046	0.105	1.575	0.782
		5		4.140	13.49***	0.987	6.979	4.153	0.964	2.993	7.067	4.420	5.724	3.619	3.981	8.487	5.214
		10		7.217	16.516	2.189	10.576	10.202	8.357	4.780	14.021	14.116	13.686	4.292	11.067	11.744	11.216
	$\Theta_{2t}^{(q3)}$	1		0.38	9.81***	1.283	0.02	13.28***	0	6.21***	0.222	0.043	0.002	0.936	0.116	0.011	0.515
		5		3.699	14.59***	2.994	0.694	20.16***	1.353	12.04**	1.745	1.410	6.324	2.856	8.102	3.760	3.088
		10		6.397	17.498	7.399	3.096	23.69***	2.492	16.374	6.474	3.311	15.101	6.750	12.180	9.229	4.098
	$\Theta_{2t}^{(q4)}$	1		9.98***	0.51	14.56***	0.476	0.121	0.194	7.3***	0.007	0.39	2.130	4.658	0.352	0.682	0.36
		5		10.66**	5.205	16.06***	5.621	2.329	5.865	10.240	8.389	2.640	6.261	10.234	13.471	4.692	9.703
		10		13.796	11.813	21.32***	10.899	10.362	7.636	13.680	16.088	9.189	10.597	11.932	14.982	9.351	15.302
	$\Theta_{2t}^{(q5)}$	1		26.54***	0.763	**15.48*** **	0.235	0.414	0.093	**9.18*** **	1.281	0.5	1.618	1.259	0.538	1.748	0.645
		5		30.04***	6.128	**21.50*** **	3.958	1.350	2.208	**12.7** **	5.722	12.506	6.203	4.740	6.904	10.162	3.178
		10		31.79***	8.319	**23.71*** **	5.719	18.576	4.121	**20.8** **	7.531	15.910	9.345	13.275	10.701	13.322	8.724

Note: ** and *** indicate that statistics are significance at the 5% and 1% level of significant respectively.

As a summary, from Table 3.34 it can be seen that there exists negative contagion from USGG2YR to BIST 100, IDX, and SENSEX. In addition, there exists flight from quality from USGG2YR to BIST 100 and SENSEX. It may be clarified that there exists weakly flight to quality from BIST 100 and MERVAL to USGG2YR. It can be stated that Latin American markets such as IPC, IPSA, and BOVESPA are dependent on U.S. bond market. Finally, one may conclude that KLCI and MERVAL are good diversification alternatives for USGG2YR.

Table 3.34 : Summary of Granger causality test results between U.S. bond market and emerging stock markets.

	Direction of causality	
Strong dependence	USGG2YR→BIST 100	
Negative contagion	USGG2YR→IDX	
Negative contagion	USGG2YR→SENSEX	
Flight from Quality	USGG2YR→SENSEX	
Negative contagion		SENSEX→USGG2YR(weakly)
Strong dependence	USGG2YR→IPC	
Strong dependence	USGG2YR→IPSA	
Negative contagion	USGG2YR→MERVAL(weakly)	
Flight to Quality		MERVAL→USGG2YR(weakly)
Strong dependence	USGG2YR→BOVESPA	

3.6 Conclusion

The goal of this essay is to determine whether there is a possibility of risk diversification between markets by determining the causal relations especially among the tail of the distributions with the help of Granger causality analysis, and by classifying the risk spillovers between Turkey and the other stock markets as financial contagion and also between stock markets and U.S. bond market as financial contagion, flight to quality and flight from quality.

In this essay, daily index values of stock exchange market indices of selected developed and emerging countries and some regional stock market indices were analyzed during the period from 01/01/2002 to 29/02/2016. And also, daily data of the U.S. two year bond yield was used to investigate financial contagion, flight to quality and flight from quality.

Firstly, contagion effects between stock markets were investigated by testing Granger causality in left tails of the stock return distributions. When analyzed regionally, one may conclude that there exists a weak contagion from SPEU to BIST 100; a bilateral contagion between S&P Africa 40 and BIST 100; and strong interdependence between SPAS 50 and BIST 100.

Furthermore, there exists negative contagion from S&P 500 and FTSE 100 to BIST 100. Moreover, there is a weak contagion from DAX 100 to BIST 100. However, the picture is different for the relationship between BIST 100 and NIKKEI 225. It can be stated that there is a weak volatility spillover from BIST 100 to NIKKEI 225 due to the causality in variance. But in the opposite direction NIKKEI 225 has no influence on BIST 100.

By analyzing causality between BIST 100 and other emerging countries, we have found that there exist negative contagion from IPC and MERVAL to BIST 100. Therewithal, it can be stated that BIST 100 is dependent on BOVESPA and IPSA by the reason of significant Granger causality in the center of the distributions. In addition, one way volatility spillover effect is observed from COLCAP to BIST 100. And for opposite direction, it can be seen that there is one way negative contagion from BIST 100 to IDX. In addition, there exists bilateral negative contagion between BIST 100 and SENSEX. Finally, there is bilateral volatility spillover between BIST 100 and MALAYSIA KLCI.

Secondly, contagion effect, flight to quality and flight from quality between stock markets and U.S. bond market was investigated. As mentioned before, flight to quality may be defined as an outflows of capital from the stock markets to the bond markets. And consistent with this definition, for each couple of asset returns (stock, bond) were tested for Granger-causality from the left-tail distribution of stocks return to the right-tail distribution of bond. By the same token, causality from the left tail of bond return distribution to the right tail of stock return distribution may be interpreted as flight from quality effect.

The results reveal that there exists contagion from the U.S. bond market to the Japan stock market. The evidence shows that the London stock market index (FTSE 100), German stock market index (DAX 100), and U.S. stock market index (S&P 500) are dependent on the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when

London stock index FTSE 100 is falling, U.S. two year bond yield (USGG2YR) is (weakly) negatively affected. Moreover, during bull market, when London stock index FTSE 100 is rising, U.S. two year bond yield (USGG2YR) is affected positively.

Finally, one may conclude that BIST 100 is dependent on USGG2YR by the reason of significant Granger causality in the center of the distributions. According to test results, it can be seen that there exists negative contagion from USGG2YR to IDX, and SENSEX. In addition, there exists flight from quality effect from USGG2YR to SENSEX. It may be clarified that there exists weakly flight to quality from MERVAL to USGG2YR. It can be stated that Latin American markets such as IPC, IPSA, and BOVESPA are dependent on U.S. bond market. To sum up, one may conclude that KLCI and MERVAL are good diversification alternatives for USGG2YR.

4. CONCLUSION

This thesis is comprised of two empirical studies on volatility transmission mechanism and risk spillovers across equity markets and U.S. bond market. First study attempts to describe the structure of the dynamic correlations between stock markets. Identifying some properties of time series such as long memory property, asymmetry effect and structural breaks is important to obtain robust estimates. For this reason, long memory property and asymmetry effects were being considered for all markets. Due to the significant long memory tests results, the most appropriate DCC-GARCH models were estimated which take into account long memory property and asymmetry effect. The most fitting model for stock markets in developed countries was AR(1)-DCC-FIGARCH(1,d,1) model under the student-t distributed innovations. To detect structural breaks in variance Kappa-2 test was employed before proceeding DCC-GARCH estimations. Only the structural break points for Latin American countries were found statistically significant and dummy variables for these variance break dates were constituted. Then, DCC-GARCH model was estimated with these dummy variables in variance.

According to estimation results, it was found the evidence of portfolio diversification opportunities between NIKKEI 225 and other developed markets. Moreover, the researcher discovered that correlations between NIKKEI 225 and FTSE 100 begin to increase in 2007 prior to the United States (U.S.) subprime mortgage crisis and at the end of 2008 it reaches its highest level when several major financial institutions collapsed in September 2008.

The evidence shows that Eurozone crisis has positive impact on the DCCs, implying that the exogenous shifts led to a rise in the volatility of the correlation between US stock market and London Stock Exchange market. This finding can be explained by the higher economic activity during these events.

In addition in August 2015 correlation between NIKKEI 225 and FTSE 100, and NIKKEI 225 and S&P 500 suddenly increase. This increase arose from the 2015–16 stock market selloff which began in the United States on August 18, 2015.

Similarly, stock market selloff has positive effect on the dynamic conditional correlations among all three markets, indicating that the exogenous shifts led to a rise in the volatility of the correlation between the Japan stock market, US stock market and London Stock Exchange market.

These results indicate that financial crisis has an effect on stock markets in developed countries. According to the definition of contagion as an increase of the correlation coefficient in a crisis period compared to a benchmark period, these findings could signal financial contagion effects between Japan and United Kingdom, and United States.

On average the correlations among Asian stock markets are less than 0.5, whereas the correlations between Malaysia and Indonesia are around 0.4. These results indicate that Asian markets are weakly correlated. Crisis dummies have a significant and positive impact on the dynamic conditional correlations between Asian stock markets, supporting the hypothesis of contagion effect. On the other hand, during tapering the coefficient of tapering dummy is statistically significant and negative, indicating that the tapering led to a reduction in the volatility of the dynamic correlations between the Asian stock markets.

Dealing with Latin American countries, it can be seen that the correlations are above 0.6 suggesting higher integration between them. The results suggest that diversification opportunities do not seem to exist between BOVESPA and MERVAL, and BOVESPA and IPC. From the estimation results of AR(1)-DCC-FIAPARCH model for Latin American stock markets during the period 2002-2016 it can be observed that the coefficients for DCC are significant except for the market pairs of MERVAL and the others.

Moreover, none of the crisis dummies in the mean equation of dynamic conditional correlations between Latin American markets is statistically significant, except selloff dummy. On the other hand, we may infer from slightly positive and significant coefficient of stock market selloff that the dynamic conditional correlations increase during this event. With regard to the variance equations, the evidence shows that global and Eurozone crisis have positive impact on the DCCs, implying that the exogenous shifts led to a rise in the volatility of the correlations between Latin American stock markets. This finding supports the hypothesis of the contagion effect. On the other hand, the coefficient of tapering dummy is statistically significant and negative, indicating that the tapering led to a reduction in the volatility of the dynamic correlations between the Latin American stock markets.

However, the second essay focuses on the causal relations especially among the tail of the distributions with the help of Granger causality analysis, and classifying the risk spillovers between Turkey and the other stock markets and also between stock markets and U.S. bond market as "financial contagion", "flight to quality" and “flight from quality”. The evidence supports financial contagion from SPEU to BIST 100; a bilateral contagion between S&P Africa 40 and BIST 100; and strong interdependence between SPAS 50 and BIST 100.

Furthermore, there exists negative contagion from S&P 500 and FTSE 100 to BIST 100. Moreover, there is a weak contagion from DAX 100 to BIST 100. However, the picture is different for the relationship between BIST 100 and NIKKEI 225. It can be stated that there is a weak volatility spillover from BIST 100 to NIKKEI 225 due to the causality in variance. But in the opposite direction NIKKEI 225 has no influence on BIST 100. Therefore, one may suggest that NIKKEI 225 and DAX 100 are good diversification alternatives for investors investing in BIST 100.

By analyzing causality between BIST 100 and other emerging countries, the evidence shows that there exists negative contagion from IPC and MERVAL to BIST 100. Having said that, it can be stated that BIST 100 is dependent on BOVESPA and IPSA by the reason of significant Granger causality in the center of the distributions. In addition, one way volatility spillover effect is observed from COLCAP to BIST 100. And for opposite direction, it can be seen that there is one way negative contagion from BIST 100 to IDX. In addition, there exist bilateral negative contagion between BIST 100 and SENSEX. Finally, there is bilateral volatility spillover between BIST 100 and MALAYSIA KLCI.

Furthermore, the results reveal that there exists contagion from the U.S. bond market to the Japan stock market. The evidence shows that the London stock market index (FTSE

100), German stock market index (DAX 100), and the U.S. stock market index (S&P 500) are dependent on the U.S. two year bond yield (USGG2YR). In conclusion only in bear market, when London stock index FTSE 100 is falling, U.S. two year bond yield (USGG2YR) is (weakly) negatively affected. Moreover, during bull market, when London stock index FTSE 100 is rising, U.S. two year bond yield (USGG2YR) is affected positively.

Finally, one may conclude that BIST 100 is dependent on USGG2YR by the reason of significant Granger causality in the center of the distributions. According to test results, it can be seen that there exists negative contagion from USGG2YR to IDX, and SENSEX. In addition, there exists flight from quality effect from USGG2YR to SENSEX. It may be clarified that there exists weakly flight to quality from MERVAL to USGG2YR. It can be stated that Latin American markets such as IPC, IPSA, and BOVESPA are dependent on U.S. bond market. To sum up, one may conclude that KLCI and MERVAL are good diversification alternatives for USGG2YR.

Overall, this dissertation draws two main conclusions. First, substantial increase in correlation is observed during crisis periods. Especially, special patterns of interdependence during the Subprime Crisis period, the European Debt Crisis period, FED Tapering and Stock market selloff period were summarized.

In conclusion, we can see that risk aversion during financial crises has an important role on direction of the investments. This study revealed that some diversification opportunities for investors. In particular, NIKKEI 225 may be an alternative investment instrument for developed stock markets. As it was mentioned before, DAX 100 and NIKKEI 225 may be offered as good alternatives for BIST 100 regarding minimizing political and market risks. And also COLCAP, IDX and MALAYSIA KLCI may be good alternatives for BIST 100.

Flight to quality occurs from Argentina to the US short-term government bond market. Especially, it appears in the American bond market because the U.S. government bond is evaluated to be the safest asset in the period of financial crisis. To sum up, one may conclude that MALAYSIA KLCI and MERVAL are good diversification alternatives for USGG2YR.

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Güloğlu B., **Kaya P.**, “Financial Contagion, Flight to Quality and Flight from the Quality among the Stock Exchange Markets of Turkey and the Developed and The Developing Countries” at ICOAEF 2016 on 5-6 December, 2016 in Girne American University, Kyrenia, North Cyprus.

Kaya P., Güloğlu B. "Analyses of Risk Spillovers, Financial Contagion, Flight to Quality and Flight from the Quality among the Stock Exchange Markets of Turkey and the Developed and the Developing Countries by the Recent Developments in the Tail Dependence Measurement" at 21st International Scientific Conference on Economic and Social Development on 18-19 May, 2017 in Belgrade, Serbia.

Güloğlu B., **Kaya P.**, Aydemir R. (2016) Volatility Transmission among Latin American Stock Markets under Structural Breaks, Physica A: Statistical Mechanics and its Applications, Vol.462, 330–340.

PROJECTS ON THE THESIS:

"Analyses of Risk Spillovers, Financial Contagion, Flight to Quality and Flight from the Quality Among the Stock Exchange Markets of Turkey and the Developed and the Developing Countries by the Recent Developments in the Tail Dependence Measurement." This project has been decided to support by TUBITAK. Project no: 116K236**.**