MODELING CO-MOVEMENTS AMONG FINANCIAL MARKETS: APPLICATIONS OF MULTIVARIATE AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY WITH SMOOTH TRANSITIONS IN CONDITIONAL CORRELATIONS

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ABSTRACT

MODELING CO-MOVEMENTS AMONG FINANCIAL MARKETS:
APPLICATIONS OF MULTIVARIATE
AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY
WITH SMOOTH TRANSITIONS IN CONDITIONAL CORRELATIONS

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The main purpose of this thesis is to assess the potential of emerging stock markets and commodity markets in attracting the attention of international investors who utilize various portfolio diversification strategies to reduce the cumulative risk of their portfolio. A successful portfolio diversification strategy requires low correlation among financial markets. However, it is now well documented that the correlations among financial markets in developed countries are very high and hence the benefits of international portfolio diversification among these markets have been very limited. This fact suggests that investors should look for alternative markets whose correlations with developed markets are low (or even negative if possible) and which have high growth potentials. In this thesis, two emerging countries' stock markets and two commodity markets are considered as alternative markets. Among emerging countries, Turkey and China are chosen due to their promising growth performance since the mid-2000s. As commodity markets, agricultural commodity and precious metal markets are selected because of the outstanding performance of the former and the "safe harbor" property of the latter. The structures and properties of dependence between these markets and stock markets in developed countries are examined by modeling the conditional correlation in the dynamic conditional correlation framework. The results reveal that upward trend hypothesis is valid for almost all correlations among market pairs and market volatility plays significant role in time varying structures of correlations.

Keywords: Multivariate GARCH, Smooth Transition Conditional Correlation, Portfolio Diversification, Financial Markets Integration and Co-movements

ÖZ

FİNANS PİYASALARI ARASINDAKİ ORTAK HAREKETLERİN
MODELLENMESİ:
KOŞULLU KORELASYON DENKLEMİNDE YUMUŞAK GEÇİŞE SAHİP
ÇOK DEĞİŞKENLİ ARCH UYGULAMALARI

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Bu çalışmanın temel amacı gelişmekte olan ülkelerdeki hisse senedi piyasalarının ve uluslararası emtia piyasalarının, uluslararası yatırımcıları kendilerine çekme potansiyellerinin değerlendirilmesidir. Portföylerinin toplam riskini azaltabilmek maksadıyla, yatırımcılar çeşitli portföy çeşitlendirme stratejilerinden yararlanırlar. Bu stratejilerin başarılı olabilmesi için portföye dâhil edilecek varlıklar arası korelasyonun düşük olması gerekmektedir. Fakat gelişmiş ülkelerin finans piyasaları arasındaki korelasyonun çok yüksek olduğu ve dolayısıyla bu pazarlar arasında yapılacak bir portföy çeşitlendirmesinin sağlayacağı faydanın çok sınırlı olacağı artık iyi bilinen bir gerçektir. Bu durum yatırımcıları gelişmiş piyasalar ile korelasyonu düşük (mümkünse negatif) ama yüksek büyüme potansiyeli olan alternatif pazar arayışına yönlendirmektedir. Bu çalışma kapsamında Türkiye ve Çin hisse senedi piyasaları ile tarımsal ürün ve değerli metal piyasaları alternatif piyasa olarak değerlendirilmiş ve bu piyasaların gelişmiş ülkelerdeki hisse senedi piyasalarıyla olan korelasyonlarının yapısı ve özellikleri dinamik koşullu korelasyonun modellenmesi ile incelenmiştir. Sonuçlar artan trend hipotezinin neredeyse tüm piyasa çiftleri arasındaki korelasyon için geçerli olduğunu ve piyasa oynaklığının (volatility) korelasyonun zaman içinde değişen yapısında önemli bir rol oynadığını ortaya koymaktadır.

Anahtar Kelimeler: Çok Değişkenli GARCH, Yumuşak Geçişli Koşullu Korelasyon, Portföy Çeşitlendirme, Finans Piyasalarının Entegrasyonu ve Ortak Hareketleri

This thesis is dedicated to

my parents Zülal and Latif

my wife Ayşegül

and my sons A.Hamza and M. Sacid

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TABLE OF CONTENTS

PLAGIARISM . . . . . **iii**

ABSTRACT . . . . . **iv**

ÖZ . . . . . **v**

DEDICATION . . . . . **vi**

ACKNOWLEDGMENTS . . . . . **vii**

TABLE OF CONTENTS . . . . . **viii**

LIST OF FIGURES . . . . . **xii**

LIST OF TABLES . . . . . **xv**

CHAPTER **1**

1 INTRODUCTION **1**

2 VOLATILITY MODELS **10**

2.1 Introduction 10

2.2 Univariate Models 11

2.2.1 ARCH Model 13

2.2.2 GARCH Model 16

2.2.3 Asymmetric GARCH models 17

2.3 Multivariate Models 20

2.3.1 Direct H_t Modeling 23

2.3.1.1 VEC-GARCH Model 23

2.3.1.2 BEKK-GARCH Model 25

2.3.2 Indirect H_t Modeling 26

2.3.2.1 CCC-GARCH Model 27

2.3.2.2 DCC-GARCH Model 29

2.3.2.3 STCC-GARCH Model 32

2.3.2.4 DSTCC-GARCH Model 36

2.3.3 Testing Constant Conditional Correlation Assumption 37

2.3.3.1 Testing against General Time Varying Conditional Correlation . . . 37
2.3.3.2 Testing against STCC-GARCH Model . . . 42
2.3.3.3 Testing for Additional Transition Function . . . 48
2.4 Modeling Cycle . . . 51
2.4.1 Test against STCC-GARCH Model . . . 53
2.4.2 Estimate STCC-GARCH Model . . . 55
2.4.3 Test for Additional Transition Function . . . 56
2.4.4 Estimate DSTCC-GARCH Model . . . 56

3 INTEGRATION OF CHINA STOCK MARKET WITH INTERNATIONAL STOCK MARKETS[1] . . . 58
3.1 Introduction . . . 58
3.2 Literature Survey . . . 60
3.3 Data and Empirical Results . . . 61
3.3.1 Data . . . 61
3.3.2 Empirical Results . . . 65
3.3.2.1 STCC-GARCH Model . . . 66
3.3.2.2 DSTCC-GARCH Model . . . 73
3.3.2.2.1 Shgh-A – S&P500: . . . 77
3.3.2.2.2 Shgh-A – FTSE: . . . 81
3.3.2.2.3 Shgh-A – CAC: . . . 85
3.3.2.2.4 Shgh-A – Nikkei: . . . 85
3.3.2.2.5 Shgh-B – S&P500: . . . 87
3.3.2.2.6 Shgh-B – FTSE: . . . 88
3.3.2.2.7 Shgh-B – CAC: . . . 90
3.3.2.2.8 Shgh-B – Nikkei: . . . 91
3.3.2.3 Comparison of Models . . . 92
3.4 Conclusion . . . 92

4 THE ORIGINS OF INCREASING TREND IN CORRELATIONS AMONG EUROPEAN STOCK MARKETS[2] . . . 95
4.1 Introduction . . . 95
4.2 Literature Survey . . . 97
4.3 Data and Empirical Results . . . 98
4.3.1 Data . . . 98

[1] Materials from this chapter are presented at the 2011 Meetings of the Midwest Econometrics Group October 6-7, The Booth of School of Business, University of Chicago.

[2] Materials from this chapter are presented at the 5th CSDA International Conference on Computational and Financial Econometrics (CFE'11) 17-19 December 2011, Senate House, University of London, UK.

4.3.2 Empirical Results . . . 102
4.3.2.1 STCC-GARCH Model . . . 103
4.3.2.2 DSTCC-GARCH Model . . . 113
4.3.2.2.1 ISX100 – DAX: . . . 113
4.3.2.2.2 ISX100 – CAC: . . . 116
4.3.2.2.3 ISX100 – FTSE: . . . 118
4.3.2.2.4 ISX100 – S&P500: . . . 118
4.3.2.3 Comparison of Models . . . 119
4.4 Conclusion . . . 121

5 THE EFFECTS OF FINANCIALIZATION OF COMMODITY MARKETS ON THE DYNAMIC STRUCTURE OF CORRELATIONS AMONG COMMODITY AND STOCK MARKET INDICES . . . 123
5.1 Introduction . . . 123
5.2 Literature Survey . . . 124
5.3 Data and Empirical Results . . . 127
5.3.1 Data . . . 127
5.3.2 Empirical Results . . . 128
5.3.2.1 STCC-GARCH Model . . . 128
5.3.2.2 DSTCC-GARCH Model . . . 132
5.3.2.2.1 S&P-AG – S&P500: . . . 132
5.3.2.2.2 S&P-PM – S&P500: . . . 138
5.3.2.3 Comparison of Models . . . 139
5.4 Conclusion . . . 139

CONCLUSIONS . . . 140

REFERENCES . . . 146

APPENDICES . . . 151
A. CCC-GARCH MODEL ESTIMATES . . . 152
B. STCC-GARCH MODEL ESTIMATES . . . 161
C. DSTCC-GARCH MODEL ESTIMATES . . . 170
D. STCC-GARCH MODEL ESTIMATES NOT REPORTED IN CHAPTERS . . . 181
E. DSTCC-GARCH MODEL ESTIMATES NOT REPORTED IN CHAPTERS . . . 217
F. ADDITIONAL TRANSITION VARIABLE TEST RESULTS NOT REPORTED IN CHAPTERS . . . 235

G. EVIDENCE OF INCREASING TREND IN CONDITIONAL CORRELATION OF CHINESE STOCK MARKETS WITH OTHERS NOT REPORTED IN CHAPTER 3 238
H. CURRICULUM VITAE 239
I. TURKISH SUMMARY 241
J. TEZ FOTOKOPISI IZIN FORMU 254

LIST OF FIGURES

FIGURES

Figure 1.1 Price Series of Major International Stock Market Indices 2

Figure 2.1 The weekly return series of ISX-100 12
Figure 2.2 Logistic function for various values of γ 34

Figure 3.1 Weekly price series of Shgh-A, Shgh-B, S&P500, FTSE, Nikkei and CAC 62
Figure 3.2 Weekly return series of Shgh-A, Shgh-B, S&P500, FTSE, Nikkei and CAC 63
Figure 3.3 The conditional correlation of Shgh-A with S&P500 and FTSE from STCC-GARCH model with time transition variable 71
Figure 3.4 The conditional correlation of Shgh-A with CAC and Nikkei from STCC-GARCH model with time transition variable 71
Figure 3.5 The conditional correlation of Shgh-B with S&P500 from STCC-GARCH model with time transition variable 71
Figure 3.6 The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of Shgh-A 77
Figure 3.7 The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of VIX 78
Figure 3.8 The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of standardized error of Shgh-A 79
Figure 3.9 The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of standardized error of S&P500 80
Figure 3.10 The conditional correlations between Shgh-A and FTSE from the DSTCC-GARCH models with time and stated second transition variables. 82
Figure 3.11 The conditional correlation between Shgh-A and CAC from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of Shgh-A 85

Figure 3.12 The conditional correlations between Shgh-A and Nikkei from the DSTCC-GARCH models with time and stated second transition variables 86
Figure 3.13 The conditional correlation between Shgh-B and S&P500 from the DSTCC-GARCH model with time and third lag of absolute value of error of Nikkei 87
Figure 3.14 The conditional correlation between Shgh-B and S&P500 from the DSTCC-GARCH model with time and time 88
Figure 3.15 The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of HSI 88
Figure 3.16 The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of S&P500 89
Figure 3.17 The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and stated second transition variables 90
Figure 3.18 The conditional correlation between Shgh-B and CAC from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of S&P500 91
Figure 3.19 The conditional correlation between Shgh-B and Nikkei from the DSTCC-GARCH model with second lag of standardized error of S&P500 and fourth lag error of Nikkei 92

Figure 4.1 Weekly price series of ISX100 in Turkey, HTX in Hungary, PX in Czech Republic, PTX in Poland, SOFIX in Bulgaria, BC in Romania, CAC in France, DAX in Germany, S&P500 in the US and FTSE in UK 100
Figure 4.2 Weekly return rates of ISX100 in Turkey, HTX in Hungary, PX in Czech Republic, PTX in Poland, SOFIX in Bulgaria, BC in Romania, CAC in France, DAX in Germany, S&P500 in the US and FTSE in UK 101
Figure 4.3 The conditional correlation of ISX100 index in Turkey with DAX and S&P500 from STCC-GARCH model with time transition variable . 104
Figure 4.4 The conditional correlation of ISX100 with CAC and FTSE from STCC-GARCH model with time transition variable 104
Figure 4.5 The conditional correlation of HTX index in Hungary with DAX and S&P500 from STCC-GARCH model with time transition variable . 106
Figure 4.6 The conditional correlation of PX index in Czech Republic with DAX and S&P500 from STCC-GARCH model with time transition variable 107
Figure 4.7 The conditional correlation of PTX index in Poland with DAX and S&P500 from STCC-GARCH model with time transition variable . 107
Figure 4.8 The conditional correlation of SOFIX index in Bulgaria with DAX and S&P500 from STCC-GARCH model with time transition variable . 108

Figure 4.9 The conditional correlation of BC index in Romania with DAX and S&P500 from STCC-GARCH model with time transition variable . 108
Figure 4.10 The conditional correlation between ISX100 and DAX from DSTCC-GARCH model with time and stated transition variables. 114
Figure 4.11 The conditional correlation between ISX100 and CAC from DSTCC-GARCH model with time and stated transition variables. 117
Figure 4.12 The conditional correlation between ISX100 and FTSE from DSTCC-GARCH model with time and second lag of absolute error of ISX100 transition variables. 118
Figure 4.13 The conditional correlation between ISX100 and S&P500 from DSTCC-GARCH model with time and stated transition variables. . . . 120

Figure 5.1 Weekly price series of S&P-GSCI Agricultural, S&P-GSCI Precious Metal and S&P500 Indices 127
Figure 5.2 The conditional correlation between S&P-AG and S&P500 from STCC-GARCH model with time transition variable 131
Figure 5.3 The conditional correlation between S&P-PM and S&P500 from STCC-GARCH model with time transition variable 132
Figure 5.4 The conditional correlation between S&P-AG and S&P500 from the DSTCC-GARCH model with time and stated second transition variable 135
Figure 5.5 The conditional correlation between S&P-AG and S&P500 from the DSTCC-GARCH model with fourth lag of conditional volatility of S&P-AG and stated second transition variable 137
Figure 5.6 The conditional correlation between S&P-PM and S&P500 from the DSTCC-GARCH model with time and stated second transition variable 138

LIST OF TABLES

TABLES

Table 3.1 Descriptive statistics of weekly return rates 63

Table 3.2 Sample correlations of weekly return rates 64
Table 3.3 Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable for Shgh-A Index 67
Table 3.4 Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable for Shgh-B Index . 68
Table 3.5 The estimation results of STCC-GARCH model with transition variable providing best fit for Shgh-A and Shgh-B indices 70
Table 3.6 LM statistics of testing additional transition variable for Shgh-A pairs 74
Table 3.7 LM statistics of testing additional transition variable for Shgh-B pairs 75
Table 3.8 The estimation results of DSTCC-GARCH models for Shgh-A . . 76
Table 3.9 The estimation results of DSTCC-GARCH models for Shgh-B . . 83
Table 3.10 Values of log-likelihood and information criteria 93

Table 4.1 Descriptive Statistics of Return Series 102
Table 4.2 Sample Correlations 102
Table 4.3 Test of Constant Conditional Correlation against STCC-GARCH model with Time Transition Variable 103
Table 4.4 The estimation results of STCC-GARCH model with time transition variable 105
Table 4.5 Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable 110
Table 4.6 LM statistics of testing STCC-GARCH model with time transition variable for additional transition variables 112
Table 4.7 The estimation results of DSTCC-GARCH models 115
Table 4.8 Values of log-likelihood and information criteria 121

Table 5.1 Descriptive Statistics of Weekly Returns 128
Table 5.2 Sample Correlations of Weekly Returns 128

Table 5.3 The LM statistics of testing constant conditional correlation against STCC-GARCH model with various transition variables. 130
Table 5.4 The estimation results of STCC-GARCH model with time transition variables. 131
Table 5.5 The LM statistics of testing estimated STCC-GARCH model for an additional transition variable. 133
Table 5.6 The estimation results of DSTCC-GARCH models with the stated transition variables 134
Table 5.7 Values of log-likelihood and information criteria 140

CHAPTER 1

INTRODUCTION

The last three decades have witnessed very dramatic financial market crashes. The first and the most influential one is the so-called "Black Monday" in October 19, 1987 when the largest one-day percentage decline in stock market history was recorded[1]. Chronologically, it is followed by the "Black Wednesday" in 1992 which caused long lasting volatility in major international financial markets. Its effects survived until the end of 1993. Then, the famous 1997 Asian financial crisis and 1998 Russian financial crisis disturbed the world financial markets and created distress. Unfortunately, the list of devastating crashes did not end and the new millennium came with new bubble of internet companies which busted in 2001 with increased volatility and big losses again. The years between 2002 and 2008 are characterized by relatively steady upward trends which were interrupted by the recent liquidity problems in the US banking system and European sovereign debt crisis leading to significant rises in volatility and making financial markets very fragile and sensitive to bad news. Although these major financial market crashes differ in terms of origins and sources, their effects generally go beyond their boundary of origin and generate high price fluctuations in most of the financial markets all around the world.

During these turmoil periods, a simple graphical inspection of daily price data from international financial markets visualizes the fact that there are simultaneous significant price changes in these markets. For example, Figure 1.1 presents the weekly price series of major developed stock market indices, namely DAX index in Germany, CAC40 index in France, FTSE index in UK and S&P500 index in the US since the first week of 2007[2]. The effects of recent financial crisis originated in the US financial market are very apparent. It seems that, although not identical, the

[1] During October, 1987 stock markets fell 45.5% in Hong Kong, 23.15% in France, 22.5% in Germany, 23% in the US and 27.3% in UK.

[2] The first observations of these series are normalized to 1 for meaningful comparison.

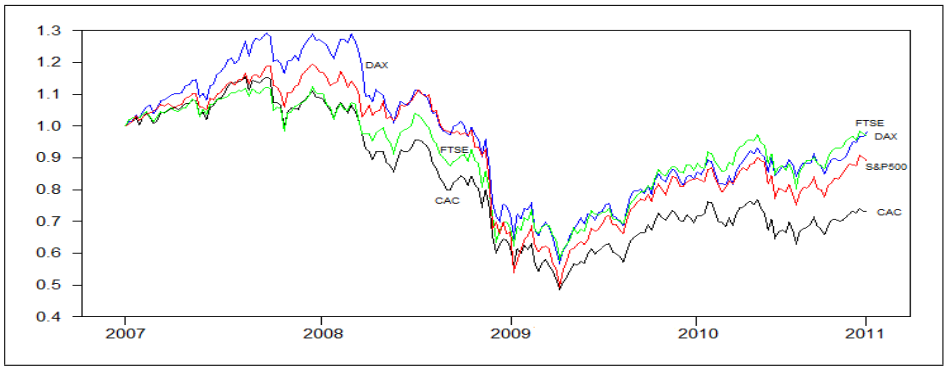


Figure 1.1: Price Series of Major International Stock Market Indices

trend governed the downturn and the recovery periods of 2008's crisis is very similar for all indices.

This type of graphical analysis supports the view that the co-movements among financial markets have been increasing and become very strong. Thus, common movements analysis has become extensively used tool in interpreting and forecasting daily performance of national financial markets by market participants, the media, and policy makers who try to rationalize price co-movements among various financial markets with the so-called factors creating the globalization process of the financial markets. These factors can be summarized as developments in information technology, establishment of multinational companies, liberalization of financial systems and capital markets (which is also responsible for the big increase in international capital flows), and abolishment of foreign exchange controls.

Although every inspection starts with it, visual examination of the data cannot be substitute for formal inspections which is necessary to confirm the inferences from visual examination. In other words, the observed increase in co-movements among financial markets should be measured and tested by formal statistical techniques. A natural statistically formal measure of co-movements is the correlation among series which is a scale free measure of interdependence. It takes values between -1 and 1 indicating negative and positive relationships, respectively. Hence, the co-movements among financial markets can be investigated formally by modeling correlation among these financial markets.

The level of co-movement or formally correlation among international financial markets has very vital implication in finance theory and it is very crucial input in financial decision making. Its importance originated from the fact that statisticians and econometricians consider the second moment as a measure of risk. Although there is no general agreement on the definition of risk, it is related to the uncertainty over future conditions mainly due to lack of full information environment and it is

generally defined as the effect of uncertainty on objectives. Investors buy and sell financial assets with the objective of maximizing their wealth. However the return from these assets depends on the future price of the underlying assets which are unknown when the decision is made. The price may increase or decrease and it is impossible to exactly predict future prices with the available information of today and past. This uncertainty over the future price of assets affects the investors' objectives and according to the definition, makes financial markets very risky.

A typical investor does not prefer to face with risk which is capable of generating unpleasant outcomes. Therefore investors need to compare available assets to choose the one with low risk and high return. With the objective of maximizing wealth, higher return is always desirable but because of the inherited risk-return trade-off in assets, it comes with higher risk level which means that risk can be thought as the cost of higher return. Therefore investors optimize their investment decision to maximize return and minimize risks.

A practical, simple and the oldest means of solution to this optimization problem can be summarized with a well-known idiom which is generated by human being wisdom of "Don't Put All Your Eggs in One Basket". This solution in its general form is applicable to any field and issues where uncertainty lies at the heart of the problem. A special form of this solution in finance theory is called "Portfolio Diversification" and formulized by Markowitz (1952) in his seminal paper of Portfolio Selection. He builds his argument on the fact that it is possible to find a bundle of assets which has collectively lower risk than any individual asset in this bundle and he shows how to find the best possible portfolio by minimizing the risk of portfolio for a given level of expected return. As a result of this minimization problem, the optimal weights of each asset in the bundle are calculated. Markowitz associates risk with variance. Thus minimizing risk is equivalent to minimum variance of the portfolio. Hence, to find the variance of the portfolio investors need the variances of all assets in this portfolio and covariance or correlations among these assets. Since the relationship between portfolio variance and correlation among assets of this portfolio is positive, portfolio diversification requires low or negative correlations to be able to attain lower risk level.

Portfolio diversification within a single market cannot eliminate systematic risk generated by common dynamics of this market or the economy in which this market operates. To reduce the domestic systemic risk, portfolio diversification strategies have been extended to international level. As shown by Solnik (1974), international diversification can provide further risk reduction due to the fact that differences exist in levels of economic growth and timing of business cycles among countries.

Therefore in order to evaluate the potential benefits of international portfolio diversification, the structure and properties of correlations among international financial

markets are very crucial for a typical risk averse investor who seeks for lower risk burden attached to higher return rates. This fact has motivated many scholars and the empirical literature has witnessed growing interest in analyzing correlations among financial markets. In the applied literature, the structures of correlation among financial markets in various countries and regions have been examined by various types of models under time varying correlation framework.

It is evident from the daily observation of financial markets but empirical results do not support increasing trend in co-movements among financial markets up to 2000s. King and Wadhwani (1990) examine the dynamics of correlations among stock market indices in UK, the US and Japan in an attempt to investigate the contagiousity of the stock markets' volatility. By using hourly return data of stock market indices over the period July 1987 to February 1988, they provide evidence that correlations among these stock market indices are time varying and the correlations tend to rise during high volatile times. To investigate the linkage and the long run properties of the correlations between stock markets, King et al. (1994) extend the scope of this correlation analysis in terms of both time interval it spans and the number of stock market index it considers. Within multivariate factor model context, they use monthly return data of 16 countries' stock markets[3] for the period from January, 1970 to October, 1988. They report that correlation is not constant and it is related to the volatility but they cannot identify a causal relation between volatility and correlation. In terms of long run properties of correlation between indices, they search for an evidence of increasing trend but they do not find any evidence over 18-year period. They conclude that the early findings[4] of increasing trend in correlations among stock market indices depend on the observations surrounding the 1987 crash and these results reflect transitory increase in correlations instead of permanent.

With high frequency data, the co-movements between stock markets in the US and Japan is examined by Karolyi and Stulz (1996) for the (post 1987 crash) period from May 31, 1988 to May 29, 1992. In addition to findings of existing literature, they reveal that large shocks to S&P500 and Nikkei positively affect the persistence of the correlations between stock market indices.

Longin and Solnik (1995) model the conditional correlations among stock market index in major developed countries, namely France, Germany, Switzerland, UK, Japan, Canada and the US for the 30-year period[5] with monthly data from January

[3] Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, UK, and the US.

[4] For example, VonFurstenberg and Jeon (1989).

[5] For a much longer period see Goetzmann et al. (2005). They investigate the correlations among almost all stock market indices over the past 150 years. They find that correlations change dramatically through time and they report three peaks; the late 19th century, the Great Depression

1960 to August 1990. In a similar work, Ramchand and Susmel (1998) use weekly[6] stock market index data from January 1980 to January 1990 to model conditional correlations between the US and major developed countries of Japan, UK, Germany and Canada. These two papers examine the dynamic structure of conditional correlation in the context of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH). The former employ multivariate GARCH(1,1) model for seven indices, while the latter use bivariate switching ARCH (SWARCH) model. Both papers find that the correlations rise in periods of high volatility. More specifically, Ramchand and Susmel (1998) report that the correlations between the US and other indices are on average 2 to 3.5 times higher when the volatility in US stock market is at high levels as compared to low levels.

These empirical results establish that the correlations among financial markets have a dynamic structure: the correlation is time varying and increases during high volatile times. However, Longin and Solnik (2001) and Ang and Bekaert (2002) report that the reaction of correlation to the volatility is asymmetric and they conclude that correlations increase during bear markets, not in bull markets.

After 2000, the findings in the literature imply that the correlations among financial markets have tended to increase over time. This result is more apparent among developed countries and among countries in the same region. The level of correlation varies from country to country and from region to region but the highest levels are attained by developed countries in European Union (EU) as reported by Cappiello et al. (2006). They investigate the correlation structure of 21 countries' stock and bond markets from Europe, America and Australasia[7] by using weekly data from January 8, 1987 to February 7, 2002. They introduce an asymmetric and generalized version of Dynamic Conditional Correlation[8] GARCH (DCC-GARCH) model of Engle (2002). They find evidence of increasing trend in correlation among financial markets mainly in Europe and they determine a structural break in correlations in January 1999 which coincides with the introduction of Euro as a single currency among the members of European Monetary System (EMS). However they conclude that the correlation among Australasian group, Americas, and Europe seem to be unaffected from the developments in Euro area. It is argued that the depreciation of

and the late 20th Century.

[6] They use thursday to thursday closing price instead of end of week closing price.

[7] European; Austria, Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and UK, Australasia; Australia, Hong Kong, Japan, New Zealand, and Singapore, and the Americas; Canada, Mexico, and US.

[8] The original DCC-GARCH model of Engle(2002) defines scalar coefficients for conditional correlation equation. Therefore country specific news impact and smoothing parameters are not allowed.

the euro vs. the US dollar right after the introduction of euro may be due to increase in correlations among stock markets of EMS member countries which led investors to diversify their portfolios less on EU countries and more on the US, in other words investors moved capital from Europe to the US according to new portfolio weights adjusted to the changes in correlation.

Unlike Cappiello et al (2006), Kim et al. (2005) employ bivariate EGARCH model with time varying conditional correlation to describe daily data of stock markets in EMS countries, Japan and the US for the period from January, 1989 to May, 2003 and find that upward trend in correlation is valid for all international markets since the introduction of Euro. Similar conclusions are obtained in Savva et al. (2009) using multivariate DCC-GARCH model for daily data of indices in UK, Germany, France and the US for the period from December, 1990 to August 2004. Compared to Cappiello et al (2006) the longer and high frequency samples in the last two papers seem to allow capturing the effects of single currency on the correlations among countries in and out of the Euro area.

Silvennoinen and Teräsvirta (2009) investigate the properties of conditional correlations among DAX, CAC40, FTSE and HSI indices with weekly data for the period from the first week of December 1990 to the last week of April 2006. They employ time varying conditional correlation approach by defining smooth transition for conditional correlation within the MGARCH framework. They find that the correlations among these stock market indices increase to higher levels in the spring of 1999. They reveal that the increasing conditional correlations between CAC-DAX, CAC-FTSE and DAX-FTSE are affected by the level of volatility since 1999. They report that with the new century, the conditional correlations between CAC-DAX, CAC-FTSE and DAX-FTSE exceed 0.9, 0.85 and 0.8, respectively and the conditional correlations between HSI and other indices reach to 0.55. In a similar work, Aslanidis et al. (2010) analyze the correlation structure between S&P500 and FTSE indices. They find evidence of increasing trend in conditional correlation and report that it increases to 0.9 around February 2000. Aslanidis et al. (2010) also investigate the role of stock market volatility and conclude that volatility plays an important role before 2000 but it loses its significance during high correlation level of 0.9.

To sum up, it is now well documented that the correlations among financial markets in developed countries are very high and the benefits of international portfolio diversification among these markets become very limited. This fact suggests that investors should look for alternative markets whose correlation with developed markets is low (or even negative if possible) and which have high growth potential.

In this thesis, two emerging countries' stock markets and two commodity markets are considered as alternative markets. Among emerging countries, Turkey and China

are chosen due to their promising growth performance since the mid-2000s. As commodity markets, agricultural commodity and precious metal markets are selected because of the outstanding performance of the former and the "safe harbor" property of the latter. The structures and properties of dependence between these alternative markets and stock markets in developed countries are examined in the context of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models to incorporate the stylized fact that the conditional correlations among financial markets are time varying. By modeling the dynamic correlations, the levels of correlation attained through time which are employed in calculation of optimal weights of portfolio diversification will have been uncovered. As well as the level, the structure and properties of dynamic conditional correlations convey valuable information for diversification strategies. If the conditional correlations of an alternative market, for example stock market in Turkey, with developed markets tend to rise during the global turmoil periods then diversifying the portfolio to Turkish stock market is more beneficial during calm periods than volatile periods. Thus, receiving capital inflow to stock market is unlikely during the global downturn periods. To this end, the role of global volatility, market specific volatility and the state of the market in describing the dynamic nature of correlations among markets are also investigated.

This thesis presents comprehensive analysis of return correlations of stock markets in Turkey and China, and agricultural commodity and precious metal markets in three independent compact chapters. Therefore it can be seen as an attempt to investigate whether these markets are able to provide opportunities to international investors in reducing the risk they bear. The plan of the thesis is as follows. The Chapter 2 discusses the both univariate and multivariate GARCH type volatility models in detail. Due to their flexibility in capturing dynamic structure of conditional correlation, the focus is particularly on Smooth Transition Conditional Correlation (STCC-GARCH) and Double Smooth Transition Conditional Correlation (DSTCC-GARCH) models proposed by Silvennoinen and Teräsvirta (2005 and 2009). The advantage and disadvantage of these models over Constant Conditional Correlation (CCC-GARCH) model of Bollerslev (1990) and Dynamic Conditional Correlation (DCC-GARCH) model of Engle (2002) are provided. Moreover, the steps of modeling cycle followed in applications are introduced in Chapter 2.

The Chapter 3 investigates the structures and properties of return correlations among Chinese stock market and stock markets in four developed countries, namely the US, UK, France and Japan. For the first time in the literature, STCC-GARCH and DSTCC-GARCH specifications are employed in modeling conditional correlations of stock markets in China. The analysis covers both A-share and B-share indices traded in Chinese stock markets. The first goal of this Chapter is to search for an evidence of increasing trend in the conditional correlations of A-share and

B-share indices with the indices in developed countries which is expected as a result of liberalization reforms took place in Chinese financial markets but has not been identified so far in the literature. Unlike earlier literature, by using calendar time as a transition variable in the STCC-GARCH model, evidences of upward trends are revealed. The other goal is to examine the role of global volatility, index specific volatility and the sign of the news from the indices on the conditional correlations by considering several measures of these factors as candidate transition variable in the context of STCC-GARCH and DSTCC-GARCH models. Empirical results imply that the correlation structure is highly affected by market volatility with volatile periods leading to lower correlations compared to the more tranquil periods for A-share index, though mixed results are obtained for B-share. Furthermore, for the first time in the literature, a structural change is detected in the response of conditional correlation between stock markets in China and the US to the lagged standardized errors which are used as default explanatory variables in the correlation equations. This fact along with the strong time trend in the conditional correlation may responsible for the poor performance of the earlier literature.

In Chapter 4, the dynamic nature of conditional correlations between Turkish stock market and stock markets in four developed countries, the US, UK, France and Germany are analyzed in two steps. Firstly, to test the increasing trend hypothesis, calendar time is used as a transition variable in modeling conditional correlation of stock market in Turkey with stock markets in EU and the US under STCC specification. Besides, this modeling procedure is also used to examine whether the increasing trend is valid for the conditional correlations of stock markets in the new members of EU. The comparison of estimation results of Turkish stock market with those of stock markets in new members is expected to shed light on the role of EU membership status on the increasing correlations and clarify the issue of whether the correlation dynamics are dominated by global factors or EU related developments. The estimation results of STCC-GARCH model with time being transition variable indicate that there is an increasing trend in the conditional correlation between all index pairs but these increasing trends seems to be irrespective of being a member. In addition, the results show that global factors seem to be more dominant in explaining increasing trends compared to EU related developments. Finally, in the second step, to address the properties of conditional correlation of Turkish stock market, the roles of global volatility, market specific volatility and the news from the markets in explaining the dynamic nature of conditional correlations among Turkish stock market and stock markets in the US, UK, France and Germany are investigated via STCC-GARCH and DSTCC-GARCH modeling framework. For Turkish stock market, these models are used for the first time in the literature. The estimation results imply that the conditional correlation of Turkish stock market with stock markets in EU are highly affected by volatility of Turkish stock market and tend to

increase during high volatile times. On the other hand, the correlation with the stock market in the US is affected by volatility of stock markets in EU and the US. The response of the correlation to volatilities in these developed stock markets changes in October 2003. Before this date the conditional correlation tends to increase in turmoil periods and after this date it tends to decline during the turmoil periods.

In order to investigate whether commodity markets are able to provide diversification benefits, Chapter 5 models the conditional correlations of stock market index in the US with two investable commodity market indices namely agricultural commodity and precious metal sub-indices within the STCC-GARCH and DSTCC-GARCH framework. The main purpose is to investigate the possible effects of the so-called "financialization of commodity markets" on the dynamic structure of the conditional correlations. To this end, this Chapter searches for evidence of increasing trend in the correlation which is expected as a result of intense interest of investors in commodity markets since 2000s. Besides, the role of global volatility, index specific volatility and the sign of the news from the indices on the evolution of conditional correlation are examined. The estimation results show that upward trend in the conditional correlation is also valid for precious metal sub-index but not for agricultural commodity sub-index. The recent surge in the conditional correlation of agricultural commodity sub-index is not a new phenomenon and seems to be temporary. The conditional correlations of both commodity sub-indices are affected by the volatility of commodity and stock market indices. The response of conditional correlation between precious metal and stock market indices to the volatility of precious metal sub-index changes in October 2008. Before October 2008, it increases during turmoil periods but after this date it decreases during turmoil periods On the other hand, the conditional correlation of agricultural commodity index tends to increase during the volatile periods of stock market and agricultural commodity indices.

Finally, Chapter 6 contains the concluding remarks.

CHAPTER 2

VOLATILITY MODELS

2.1 Introduction

The risk-return trade-off inherent in all economic decisions necessitates the understanding of the nature of risk generated by the uncertainty on the future. The risk of assets, portfolios or markets is represented by the term of volatility which cannot be observed. The main workhorse tools suggested by finance theory to deal with risk are assumed that the concept of volatility can be precisely measured by second moments and consider square root of variance as a measure of volatility. However, Granger (2002) discusses the validity of this assumption and points out that variance can be a successful risk measure if utility function is quadratic or if the return distribution is normal or log-normal. Based on the works of Harter (1977), Money et al (1982), Nyquist (1983), Ding et al (1993) and Granger (2000), he suggests[1] to use mean absolute deviation ($E(|return - mean\ return|)$) to measure risk since most of the financial series have excess kurtosis relative to normal distribution as established by Mandelbrot (1962). Although the debate on risk measurement goes on theoretical ground, in empirical literature appropriate modeling of variance, covariance or equivalently correlation is of interest.

Statisticians and econometricians propose various models to estimate variance. If the volatility is constant, the traditional econometric methods can successfully estimate a measure of volatility, variance, together with mean equations. Unfortunately, in financial time series, volatility is not constant through time at least in the short-run, which is the main concern of investors due to the fact that no one wants to hold an asset forever. Thus an accurate measure of volatility should be incorporate the time varying nature of volatility.

[1] Granger strictly suggests the use of absolute returns due to its stable structure. Because the variance of a variance corresponds to fourth moments of returns, which will be very unstable, and the variance of absolute returns is just the variance of a return, and expected to be more stable as its nature implied.

The seminal paper of Engle (1982) proposes Autoregressive Conditional Heteroscedasticity (ARCH) models and shows that mean and time varying variance of series can be jointly estimated with autoregressive moving average (ARMA) models. In univariate context, ARCH, its generalized version GARCH and their extensions are very successful in describing and forecasting the time varying variance of a single financial time series. It is obvious that it is not only the conditional variance that changes with time but also conditional covariance and correlation may change through time. Thus, covariance or correlations which are required by co-movement analysis and portfolio diversification strategies have to be examined under the time varying structure. The extension of ARCH/GARCH type models to multivariate analyses proposes a prosperous means of modeling time varying covariance among financial assets and markets along with time varying variance of these assets and markets. Besides, multivariate GARCH (MGARCH) models take the interactions among financial markets in to account and therefore allow to describing more realistic and adequate empirical models.

In this chapter, ARCH/GARCH models which prove their success in modeling time varying variance, covariance and correlation are explained in detail. The second Section deals with univariate ARCH/GARCH models and the third Section continues with multivariate extensions of these models. Finally, the modeling procedure followed in Chapters 3, 4 and 5 are introduced.

2.2 Univariate Models

The Figure 2.1 presents the weekly return series of Istanbul Stock Exchange 100 index (ISX-100) for the period from 1994 to 2011. Two important stylized facts which are also observed in most of the financial series, can easily be noticed. The first one is that the volatility of the ISX-100 is not constant. Second, there are volatility clusters through time: i.e. for some periods volatility stays at high levels (high volatility is followed by high volatility) and for some periods it is relatively stable.

For example, volatility is very high between 1998 and 1999. Very large positive and negative returns occur in these years. The volatility comes back to low values since 2000 but this tranquil period lasts for a very short time. Between the years 2001 and 2003 volatility again is very high. After 2003, it is relatively calm until the global financial crisis in 2009. Therefore a successful variance model must incorporate this dynamic nature of volatility through time.

The proposition comes from Engle (1982) while he was looking for a model with time varying variance to test the effect of inflation uncertainty on the business cycles. Time varying variance is not a new concept in the econometrics and it is known as

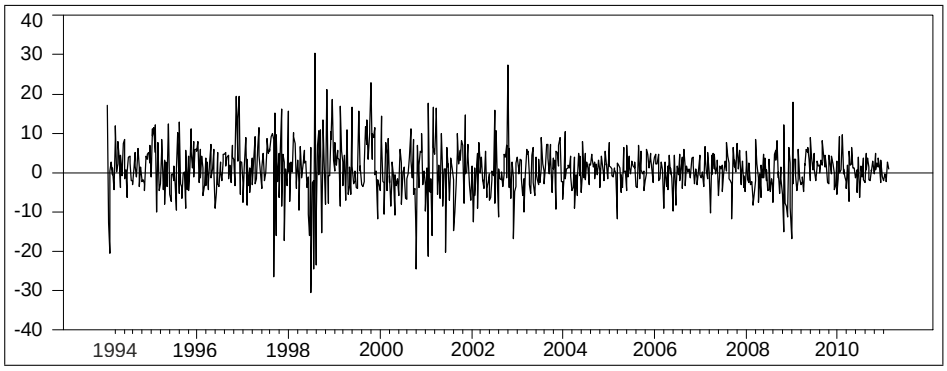


Figure 2.1: The weekly return series of ISX-100

heteroscedasticity in the regression framework. However in conventional model it is defined as some function of independent variables: i.e. the variance is larger when the independent variable is larger. The breakthrough of ARCH/GARCH model is that conditional variance can be modeled along with the conditional mean (Engle, 2003).

Two points deserve further explanation. The first one is that this new model emphases conditional variance instead of unconditional variance. It is originated from the fact that a typical investor buys and holds an asset to make profit in the future. Therefore the related risk for this investor is the risk he bears during the holding period of this asset. Thus the investor is not interested in the long run unconditional variance of this asset. A rational investor must use all available information which means that mean and variance are predicted using all available information. Thus conditional matters, not unconditional one. Besides, conditional approach provides very important implication for estimation. Any likelihood function can be decomposed into its conditional densities. Thus with conditional variance the likelihood function is easy to formulate and maximum likelihood estimation is easy to manage (Engle, 1995). Another point is that although conditional variance is time varying it is possible to have constant unconditional variance. This provides feasible and meaningful estimation because if the unconditional variance of a series is not constant, the series is nonstationary. However conditional heteroscedasticity is not a source of nonstationarity (Bollerslev et al. (1992)).

The second point in ARCH is that it formulates conditional variance as autoregressive (AR), moving average (MA) or autoregressive moving average (ARMA) process. This point is motivated from the earlier finding of Granger that squared and absolute values of series are autocorrelated even if the series itself is not. The meaning of this finding in regression framework is that even if the residuals are not autocorrelated, the squares of residual or absolute value of residual are autocorrelated. This case is valid for many variables. This finding has a very crucial implication that the error

variance can be predictable. A regression equation consists of a systematic component and a random component The former is predictable but the latter is not. The ARCH model makes the variance of this unpredictable component (i.e. residual) predictable. Since the mean of most of the financial series are very close to zero the residuals are more easily estimated with ARCH models in financial series (Engle, 1995).

The initial ARCH model proposed by Engle (1982) has extended to cover many different properties of financial time series. The main models are explained below with their properties.

2.2.1 ARCH Model

In its general form, consider the stochastic process

$$y_t = \mu x_t + u_t \tag{2.1}$$

Define an information set Ψ_{t-1} which contains all available information up to time $t-1$. The conditional mean of y_t is μx_t where x_t may contain exogenous or lagged dependent variables which are included in Ψ, and μ is the vector of parameters. Thus the conditional mean of y_t is a linear combination of exogenous or lagged dependent variable in its general form.

Engel (1982) defines conditional variance as a linear function of past squared errors. The use of lagged squared errors in the conditional variance equation does not mean that they are causes of volatility, instead they are employed to represent the true causes of conditional variance and to improve the model performance in describing the conditional variance. Within the ARCH framework the causes and consequences of volatility can be examined and tested. By inserting the relevant variables into the variance equation, the causes of volatility can be determined. Similarly by incorporating the conditional variance in to mean or other variance equations as an explanatory variable, consequences of volatility can be examined. If the true causes of variation could be identified then the lagged squared errors became redundant and statistically insignificant (Engle, 2003). However, in application lagged square errors have become default variables without any search for appropriate explanatory variables for conditional variance equation.

For simplicity consider ARCH(1) process

$$u_t = \varepsilon_t \sqrt{h_t} \tag{2.2}$$

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{2.3}$$

where ε_t is independent and identically distributed with mean *zero* ($E(\varepsilon_t) = 0$) and variance *one* ($E(\varepsilon_t^2) = 1$). Given that ε_t and u_{t-1} are independent, the error term in the mean equation (u_t) has zero unconditional and conditional mean, and it is serially uncorrelated by definition.

$$\begin{aligned} E(u_t) &= E(\varepsilon_t \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2}) \\ &= E(\varepsilon_t) E(\sqrt{\alpha_0 + \alpha_1 u_{t-1}^2}) = 0 \end{aligned}$$

$$\begin{aligned} E(u_t|\Psi_{t-1}) &= E(\varepsilon_t \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2}|\Psi_{t-1}) \\ &= E(\varepsilon_t|\Psi_{t-1}) \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2} \\ &= E(\varepsilon_t) \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2} = 0 \end{aligned}$$

$$\begin{aligned} E(u_t u_s) &= E(\varepsilon_t \sqrt{\alpha_0 + \alpha_1 u_{t-1}^2} \varepsilon_s \sqrt{\alpha_0 + \alpha_1 u_{s-1}^2}) \qquad t \neq s \\ &= E(\varepsilon_t \varepsilon_s) E(\sqrt{\alpha_0 + \alpha_1 u_{t-1}^2} \sqrt{\alpha_0 + \alpha_1 u_{s-1}^2}) = 0 \end{aligned}$$

The conditional variance of u_t is h_t;

$$\begin{aligned} E(u_t^2|\Psi_{t-1}) &= E(\varepsilon_t^2(\alpha_0 + \alpha_1 u_{t-1}^2)|\Psi_{t-1}) \\ &= E(\varepsilon_t^2)(\alpha_0 + \alpha_1 u_{t-1}^2) \\ &= (\alpha_0 + \alpha_1 u_{t-1}^2) \end{aligned}$$

The unconditional variance of u_t is

$$\begin{aligned} E(u_t^2) &= E(\varepsilon_t^2(\alpha_0 + \alpha_1 u_{t-1}^2)) \\ &= E(\varepsilon_t^2) E(\alpha_0 + \alpha_1 u_{t-1}^2) \\ &= E(\alpha_0 + \alpha_1 u_{t-1}^2) \\ &= \frac{\alpha_0}{1 - \alpha_1} \end{aligned}$$

following the fact that $E(u_t^2) = E(u_{t-1}^2)$.

Therefore the ARCH process defined by Engle has constant unconditional variance but time varying conditional variance which is not a source of nonstationarity. However to make unconditional variance finite which is required for the stability of process α_1 must be restricted to be less than *one* ($\alpha_1 < 1$)[2]. Since variance can not

[2]The generalization of this condition to ARCH(q) process is straightforward; $\sum_i^q \alpha_i < 1$

be nonpositive, α_1 must be greater or equal to *zero* ($\alpha_1 \geqslant 0$) and α_0 must be greater than *zero* ($\alpha_0 > 0$)[3].

The conditional variance equation defined as a linear function of past squared errors is equivalent to a type of weighted variance which is equal to weighted average of past squared errors. Thus ARCH model of volatility is a kind of *historical volatility* which is a rolling window estimation of volatility from square root of sample variance over a particular period. For example 30-day rolling window estimate of volatility is calculated by square root of sample variance from the last 30 observations. The successive estimate of variance is calculated by dropping 30^{th} observation and adding the recent observation and keeping total number of observation at 30. However, in this calculation it is assumed that all predetermined past observations have identical weights which means that they have identical effect. The choice of period length is also problematic in this calculation; it is not clear why 30-day should be preferred to for example 50-day. However in the ARCH model which is also based on the weighted average calculation, the length of period and the weights are determined by the data at hand. This procedure makes it possible that recent observations have more influence than distant past observations. Thus ARCH method propose a rule based objective sample variance estimation driven by data (Engle, 2007).

The ARCH process described by the Equation 2.3 satisfies the two stylized facts discussed with the help of Figure 2.1 above. The conditional variance is time varying and it have clusters. If the realization of u_{t-1}^2 is large then the conditional variance in time t will be large.

The ARCH model can be easily estimated with maximum likelihood (ML) method. Under the normally distributed errors, the log-likelihood is

$$\sum_{t=1}^{T} \ell_t = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(h_t) - \frac{1}{2}\sum_{t=1}^{T} u_t^2/h_t \tag{2.4}$$

where u_t contains parameters of mean equation and h_t contains the ARCH parameters. Since the parameters are in nonlinear form there is no closed form solution for parameters and iteration process is required to estimate parameters.

In application, more than four lagged squared errors may appear as statistically significant explanatory variable in the conditional variance equations. It is very difficult to impose positive variance and stability restrictions on α and without imposing these restrictions, the unrestricted model generally fails to satisfy these restrictions. Instead, a linearly declining set of weights are assumed and the variance

[3] α_0 can not be *zero*. Otherwise unconditional variance would be equal to *zero*.

equation is reduced to two-parameter equation. A process containing four lagged squared errors with linearly declining weights is considered by Engle as

$$h_t = \alpha_0 + \alpha_1(0.4u_{t-1}^2 + 0.3u_{t-2}^2 + 0.2u_{t-3}^2 + 0.1u_{t-4}^2) \tag{2.5}$$

The sufficient conditions of Equation 2.3 for positive variance and stability are also sufficient for Equation 2.5. However as it was discussed for historical volatility measure, the weighting scheme can not be justified. The solution to this problem is proposed by Bollerslev (1986). As an analogue of the parsimony offered by ARMA model to large number of parameter problem in AR model, Bollerslev formulates conditional variance as an ARMA process and his approach is discussed below.

2.2.2 GARCH Model

Instead of defining linearly declining predetermined weights, Bollerslev (1986) considers a geometrically declining weights scheme with a rate which is estimated from the data and he defines the conditional variance as a function of these weights. Thus Bollerslev generalizes an autoregressive[4] process to an autoregressive moving average process. He formulates the conditional variance as GARCH(1,1) process as;

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{2.6}$$

where the persistence of conditional variance is governed by a single parameter, β_1. The GARCH model improves the performance of ARCH model in defining volatility dynamics. GARCH(1,1) model is very successful and has become very popular in almost all applications. For GARCH(1,1) case[5] the conditions $\alpha_0 > 0, \alpha_1 \geqslant 0, \beta_1 \geqslant 0$ and $\alpha_1 + \beta_1 < 1$ are sufficient to guarantee the positive variance and stationary process.

---

[4] At first glance the ARCH process looks like MA specification rather than AR. Because the conditional variance is a moving average of squared residuals. To see why ARCH is AR and GARCH is ARMA, consider the GARCH(1,1) in Equation I and reparametrization of it in Equation II given below:

$$h_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{I}$$

$$u_t^2 = \alpha_0 + (\alpha_1 + \beta_1)u_{t-1}^2 - \beta_1(u_{t-1}^2 - h_{t-1}^2) + (u_t^2 - h_t^2) \tag{II}$$

Equation II expresses the GARCH(1,1) in squared errors. The ARCH parameters (α) appear in only AR term of this equation which means that ARCH defines an AR process in squared errors. However, GARCH parameters (β) appear in both AR and MA terms which means that GARCH creates ARMA effects in square errors (Engle 1995).

[5] For a general GARCH(p,q) process

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2$$

to have positive variance and stationarity properties all α_i and β_j must be nonnegative and α_0 must be positive, and $\sum_i \alpha_i + \sum_j \beta_j < 1$ must hold.

One of the main advantage of GARCH(1,1) specification is that it is very easy to understand and interpret the parameters. The conditional variance in any period is the weighted average of a constant which correspond to long run unconditional variance, square of previous period error and the previous period's conditional variance. The squared error belongs to previous period is not available when the forecast of previous period's conditional variance was made. Therefore this period conditional variance is based on one period error and all other errors are used in conditional variance of previous period. If the squared errors are considered as the arrival of new information[6], GARCH model updates previous period's conditional variance with new available information represented by squared errors. Thus, GARCH models can be thought as a type of learning procedure. The weights in conditional variance equation determine how fast the variance responds to new information and how fast it returns to its unconditional (long run) variance (Engle, 2003).

Various generalization of GARCH model have been proposed in the literature. There are a lot of survey papers summarizing the large number of model proposed for different purposes. Among them, the leading survey papers are Bollerslev, et. al. (1992), Bera and Higgins (1993), Bollerslev (1994), Pagan (1996), Palm (1996), Shephard (1996), Engle (2002), and Engle and Ishida (2002). Among various generalization of GARCH models, most important generalization is the asymmetric GARCH models.

2.2.3 Asymmetric GARCH models

Since the conditional variance equation contains the squared errors, the model can not recognize the difference between positive and negative errors of same magnitude by construction. In financial context, it is expected that investors are more sensitive to negative errors than positive ones. Therefore most probably they put more weight to negative errors than positive errors which means that negative returns predict higher volatility. This fact is known as *financial leverage* and it is first recognized by Exponential GARCH (EGARCH) model of Nelson (1992).

The EGARCH(1,1) model;

$$\ln(h_t) = \alpha_0 + \gamma(\frac{u_{t-1}}{\sqrt{h_{t-1}}}) + \alpha_1(|\frac{u_{t-1}}{\sqrt{h_{t-1}}}| - E[|\frac{u_{t-1}}{\sqrt{h_{t-1}}}|]) + \beta_1 \ln(h_{t-1}) \quad (2.7)$$

$$= \ln(h_t) = \alpha_0 + \gamma(\varepsilon_{t-1}) + \alpha_1(\ |\varepsilon_{t-1}| - E[\ |\varepsilon_{t-1}|\ ]\ ) + \beta_1 \ln(h_{t-1}) \quad (2.8)$$

Motivated from the fact that the error made in calm periods may have distinct effect on volatility than the error made in turmoil periods, this model weights errors with their associated conditional variance and uses standardized errors ($\varepsilon_t = u_t/\sqrt{h_t}$),

[6] The reason of making an error is the lack of full information. Therefore the error correspond to correction, if full information was available.

which is an unit free measure, instead of using errors (u_t) itself. Thus, the use of standardized errors in the log-variance equation tends to mitigate the effect of large shocks. Nelson argues that the interpretation of magnitude and persistency of shocks are more relevant in this framework. In logarithmic specification of conditional variance equation, the second term, ε_{t-1}, is mean zero shock and the absolute value of lagged errors, $|\varepsilon_{t-1}|$, is transformed to mean zero shock by the third term, ($|\varepsilon_{t-1}| - E[\ |\varepsilon_{t-1}|\ ]$). Since both shocks have zero mean which makes logarithmic specification an autoregressive (AR) process, the process is stationary if the condition $\beta_1 < 1$ is satisfied.

With this formulation two improvements over GARCH specification are achieved. The first one is; there is no need to restrict the parameters to be greater than *zero* to make conditional variance positive for all t. Logarithmic formulation allows for negative parameters which may make $\log(h_t)$ negative for some or all t. Since antilogarithm of any positive or negative number is always positive, conditional variance, h_t is always positive for all t. The second advantage of EGARCH is that it recognizes the asymmetric respond with respect to the sign of error[7]. When the error is positive then its effect on logarithm of conditional variance is $\alpha_1 + \gamma$ and when it is negative its effect is $\alpha_1 - \gamma$. Therefore the γ parameter determines the difference between positive and negative shocks of equal magnitude and if γ is negative then the expectation of negative errors or in other words bad news lead to higher volatility can be justified by data.

In addition to EGARCH, GJR-GARCH model of Glosten et al (1993), Threshold GARCH model of Zakoian (1994) and Smooth-Transition GARCH model of González-Rivera (1998) formulize the conditional variance to catch possible asymmetric respond of volatility with respect to the sign of the error.

The GJR-GARCH(1,1) model:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma I[u_{t-1} < 0] u_{t-1}^2 + \beta_1 h_{t-1}$$

where $I[u_{t-1} < 0]$ is an indicator function which takes on value *one* if the statement is true; i.e. $u_{t-1} < 0$. In fact GJR-GARCH model is a kind of threshold model with implicit assumption of threshold value is *zero*. Zakoian (1994) formulates a threshold model which is very similar to GJR-GARCH model but he defines square root of conditional variance instead of conditional variance to be able to use absolute value of lagged errors which have less responsive nature relative to squared lagged errors.

[7] In fact the EGARCH model is defined to recognize the asymmetric respond with respect to standardized error. However, since the square root of conditional variance, h_t is always positive, the sign of error and standardized error are the same.

The threshold GARCH(1,1) model:

$$\sqrt{h_t} = \alpha_0 + \alpha_1|u_{t-1}| + \gamma I[u_{t-1} < 0]|u_{t-1}| + \beta_1\sqrt{h_{t-1}}$$

In these two models, bad news associated with negative errors have $\alpha_1 + \gamma$ effect and good news have α_1. Thus, asymmetric effect is captured by γ parameter and if γ is positive then bad news produce higher volatility.

Instead of assuming all negative errors have a particular common effect and all positive errors have another particular common effect on volatility and instead of defining all dynamics with two parameters, the smooth transition GARCH model of González-Rivera assumes that there are two extreme and regime specific parameters; one is associated with the most negative error and other one is with the most positive error. The values of error which are between these two extreme errors have an effect which is a linear combination of these two regime specific extreme parameters as a function of observable transition variable. The model is as follows;

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma u_{t-1}^2 F(u_{t-d};\delta) + \beta_1 h_{t-1}$$

where $F(u_{t-d};\delta)$ is a monotonic transition function which is assumed to be logistic function in ST-GARCH model and it is defined as $F(u_{t-d};\delta) = [(1+\exp(\delta u_{t-d}))^{-1} - 1/2]$ to take on values between $-1/2$ and $1/2$. u_{t-d} is the transition variable and δ determines the speed of transition. The most negative value of u_{t-d} has an $(\alpha_1 + \frac{\alpha_2}{2})$ effect on conditional variance and the most positive value of it has an $(\alpha_1 - \frac{\alpha_2}{2})$ effect. Other negative values of u_{t-d} between the most negative one and *zero* have an effect between $(\alpha_1 + \frac{\alpha_2}{2})$ and α_1. Other positive values of u_{t-d} between *zero* and the most positive one have an effect between α_1 and $(\alpha_1 - \frac{\alpha_2}{2})$.

These major univariate models described here together with other variant of GARCH models have become the workhorse of volatility modeling and they are widely used to model time varying variance of financial time series. However, as discussed above, to assess the significance of the increase in the dependence of financial markets and to be able to employ the strategies proposed by finance theory to deal with risk, time varying covariance or equivalently time varying correlation between financial assets or markets are required. Inspired by the success of univariate GARCH models in describing and forecasting the time varying variance of financial time series, the appropriate formulation of dynamic covariance or correlation which comes to mind first is the extension of univariate GARCH models to multivariate GARCH models which are discussed below.

2.3 Multivariate Models

The main focus of the thesis is on the direct co-movement interpretation of correlation among financial markets and on the international portfolio diversification strategies in which covariance or correlation is very crucial input to evaluate the importance of emerging stock markets and commodity markets. Portfolio diversification is one of the oldest methods of reducing risk and is based on the idea of diversify your investment on a bundle of assets, instead of investing all of your wealth in a single asset. Markowitz (1952) indicates that a bundle of assets (portfolio) can have collectively lower risk than any individual asset in this bundle due to the fact that assets are not identical and they have different characteristics. As a measure of portfolio risk, Markowitz employs variance of this portfolio which depends on the variances of assets and covariances among these assets. Therefore, if the covariances among these assets are known then, the optimal weights can be calculated to minimize the risk burden attached to a particular return level. These optimal weights determine the share of each asset in the portfolio. As well as the conditional variance, the conditional covariance and correlation may have dynamic structure and time varying nature of variance of assets and covariance among assets imply that static particular portfolio weights may lose its optimality through time. Therefore portfolio weights must be updated according to changes in variance and covariance. A natural means of modeling time varying conditional covariance and correlation is to employ multivariate extension of univariate GARCH models which are very successful in describing and forecasting the time varying variance of financial time series. An analogue to univariate GARCH models, multivariate GARCH (MGARCH) models are supposed to be successful in describing and forecasting the time varying structure of covariance among financial time series along with time varying variance. The dynamic variance-covariance matrix characterized by MGARCH models provides the necessary input to update asset weights in portfolio diversification.

Besides, the MGARCH models have very practical implication for Capital Asset Pricing Model (CAPM) of Sharpe (1964). Similar to the portfolio selection theory of Markowitz, Sharpe (1964) uses variance as a measure of risk. Markowitz proposes a rationale means of finding the lowest risk level associated to a particular return level which is chosen by investors. But this theory cannot say anything about whether the investors get the fair rewards as a return to risk they bear. This issue is addressed by CAPM which is a model for pricing an individual asset or a portfolio. Risk is measured relative to market return; therefore CAPM recognizes the distinction between systematic risk (undiversifiable risk) and unsystematic risk (It is also known as idiosyncratic risk or diversifiable risk.). Since CAPM defines relative riskiness of an asset with the ratio of covariance between the asset and market returns to variance

of the market return, variance-covariance matrix of asset returns is needed. The so-called β parameter in this model is a measure of relative riskiness of an asset relative to market and is equal to the ratio of covariance between asset return and market return to the variance of market return. The CAPM assumes that β is constant over time. The MGARCH formulates time varying properties of variance and covariance which means that MGARCH is able to model time varying β.

In addition to the need for modeling covariance or correlation, a second motivation behind the extension of univariate GARCH models to MGARCH is the fact that the results and conclusions from separate univariate GARCH models are realistic and reliable under the assumption that there is no significant interaction among financial variables. In other words, the covariances among financial series are close to zero. However, the observation of simultaneous high changes in the financial markets due to developments in information technology, establishment of multinational companies, and liberalization of financial systems and capital markets leads to the widely accepted conclusion that the covariances among financial assets and markets are strong. Thus separate analyses are not adequate anymore. This fact leads to multivariate analysis in which jointly evolving processes can be modeled and more realistic and adequate empirical models can be built.

There are three important issues in designing MGARCH parametrization. Unlike univariate models, conditional covariance has to be modeled together with conditional variance in multivariate framework. Thus the number of equations in variance-covariance matrix increases rapidly as the number of assets in the model increases. If each equation is defined too flexible to be able to represent the many dynamics then each equation consists of many parameters and therefore total number of parameters in conditional variance-covariance matrix becomes too many which makes estimation procedure very challenging and time consuming task with unstable results. Therefore the first important issue in designing MGARCH model is to optimize parsimonious property with flexibility. The second issue is concerned with the positive definiteness of conditional variance-covariance matrix. By definition of regular variance, the variance-covariance matrix has to be positive definite for all t. Most of the time, it is very difficult to impose necessary restrictions to guarantee the positive definiteness of this matrix. Finally, MGARCH model should be constructed in a way that the likelihood function become easy to manage. Since the model has nonlinear fashion, there is no closed form solution for parameters and numerical optimization has to be employed. As in the univariate case, maximum likelihood estimation technique is used and likelihood function contains inverse of time varying variance covariance matrix. This requires inverting this matrix in each iteration for all t during numerical optimization. In following sections various MGARCH models are described in detail and they are evaluated according to these three issues.

MGARCH modeling starts with defining mean equations of stock returns. As in the univariate case, the mean equations can be so general to represent wide range of data generating processes in multivariate GARCH models. They can be in the form of vector autoregressive (VAR) or error correction model (ECM). For the sake notational simplicity, consider the stochastic N dimensional vector process

$$y_t = \mu_t + u_t \tag{2.9}$$

where y_t is an $N \times 1$ vector of returns, μ_t is an $N \times 1$ vector of conditional means of returns which can be a function of exogenous or lagged dependent variables. The standard MGARCH model defines the error as

$$u_t = H_t^{1/2} z_t \tag{2.10}$$

where $H_t^{1/2}$ is an $N \times N$ positive definite matrix for all t and z_t is an $N \times 1$ vector such that $E(z_t) = 0$ and $var(z_t) = I_N$ which is an $N \times N$ identity matrix. Define an information set Ψ_{t-1} which contains all available information up to time $t-1$ then conditional variance covariance matrix of u_t is

$$\begin{aligned} var(u_t|\Psi_{t-1}) &= var(H_t^{1/2} z_t|\Psi_{t-1}) \\ &= H_t^{1/2} var(z_t|\Psi_{t-1}) H_t^{1/2} \\ &= H_t \end{aligned}$$

In univariate case H_t consists of one variance and it can be defined as $H_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 H_{t-1}$. However in multivariate context H_t is an $N \times N$ symmetric matrix and contains N variance on diagonals and $N(N-1)/2$ unique covariance, so defining H_t is not straightforward as in the case of univariate GARCH. With MGARCH models the time varying conditional correlation which is the main concern of this thesis can be obtained by two methods. In the first method, conditional variance and covariance elements of H_t are modeled directly and conditional correlation is calculated from these variances and covariances. The second method models the conditional correlation directly therefore covariance, so H_t, is modeled indirectly. In the literature various parametrization of conditional variance covariance matrix, H_t, are proposed and it is possible divide these parametrization in to two main groups. The models in the first group define covariances directly. In the second group, the models define conditional correlation instead of conditional covariance. In other words, the first group models conditional variance covariance matrix directly while the second group does indirectly.

2.3.1 Direct H_t Modeling

2.3.1.1 VEC-GARCH Model

The first MGARCH model is proposed by Bollerslev, Engle, and Wooldridge (1988). Their model is a direct generalization of the univariate GARCH model. Each conditional variance and covariance are defined as a function of all lagged conditional variances and covariances, as well as lagged squared errors and cross-products of lagged errors. They use half-vectorization operator of vech and call this model VEC-GARCH.

$$vech(H_t) = C + \sum_{i=1}^{q} A_i vech(u_{t-i}u'_{t-i}) + \sum_{j=1}^{p} B_j vech(H_{t-j}) \tag{2.11}$$

where C is an $N(N+1)/2 \times 1$ vector, and A and B are $N(N+1)/2 \times N(N+1)/2$ parameter matrices and $vech()$ is an operator that stacks only the columns from the principal diagonal of a square matrix downwards in a column vector, i.e.

$$H = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \qquad vech(H) = \begin{bmatrix} h_{11} \\ h_{21} \\ h_{22} \end{bmatrix}$$

For example, VEC parametrization of bivariate GARCH(1,1) model is

$$\begin{aligned} vech(H_t) \quad = \quad \begin{bmatrix} h_{11,t} \\ h_{21,t} \\ h_{22,t} \end{bmatrix} &= \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} u^2_{1,t-1} \\ u_{1,t-1}u_{2,t-1} \\ u^2_{2,t-1} \end{bmatrix} \\ &\quad + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{21,t-1} \\ h_{22,t-1} \end{bmatrix} \end{aligned} \tag{2.12}$$

where $h_{ii,t}$ and $h_{ij,t}$ correspond to variance of series i and covariance between series i and j respectively. Therefore conditional variance of first series is defined as

$$\begin{aligned} h_{11,t} \quad = \quad & c_1 + a_{11}u^2_{1,t-1} + a_{12}u_{1,t-1}u_{2,t-1} + a_{13}u^2_{2,t-1} \\ & + b_{11}h_{11,t-1} + b_{12}h_{21,t-1} + b_{13}h_{22,t-1} \end{aligned} \tag{2.13}$$

which is a function of lagged squared errors of each series, cross product of lagged errors of each series, lagged conditional variance of each series and covariances between series. Thus while univariate GARCH models assume that conditional variance is effected by its own lagged conditional variance and lagged square of own error, the VEC formulation takes the effect of lagged conditional variance, covariance and lagged squared errors of other series into consideration. Therefore in this framework

it is possible to test whether volatility of one market or shocks in one market is capable to affect the volatilities in other markets. For example, in bivariate VEC-GARCH(1,1) model the parameter b_{13} indicates the effect of second series' variance from previous period on the variance of the first series. It is also possible to test whether the variance of one series affects the variance of other series directly i.e. through variance via b_{13} parameter or indirectly i.e. through covariance via b_{12}. Although VEC-GARCH model defines covariance directly, time varying correlation between series can be generated by calculating conditional correlation for each t from the estimated variance and covariance series.

The flexible structure of VEC-GARCH model leads to rapid increase in the number of parameters when the dimension of the model increases. There are $(p+q)(N(N+1)/2)^2 + N(N+1)/2$ parameters in conditional variance covariance matrix in its general form. If the fact that GARCH(1,1) model in univariate case is sufficient for most of the case is considered, the summation of $(p+q)$ reduces to 2. Then total number of parameters for the case of two series, three series and four series is 21, 78 and 210 respectively. Thus, it is almost impossible to estimate a VEC-GARCH(1,1) model for more than four series. Therefore it is not practical in terms of the first issue of constructing parsimonious model. Besides, it is difficult to impose restrictions to guarantee the positive definiteness of H_t. Instead of necessary conditions, only restrictive sufficient conditions are exist for VEC model. Thus it is not practical in terms of the second issue to ensure positive definiteness of H_t. Finally when the estimation procedure is considered, the log-likelihood of VEC-GARCH model in the Equation 2.11 under the multivariate normality assumption of u_t is

$$\sum_{t=1}^{T} \ell_t = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(|H_t|) - \frac{1}{2}\sum_{t=1}^{T} u_t' H_t^{-1} u_t \tag{2.14}$$

As mentioned above, due to nonlinear form of the model there is no closed form solution for model parameters and the log-likelihood in Equation 2.14 is maximized by numerical optimization through iterations. This numerical optimization requires inverting the matrix H_t for all t in each iteration. Together with large number of parameters, this become very challenging task when the number of observation (i.e. T) and the number of asset (i.e. N) are large. Thus VEC parametrization of H_t matrix have problematic estimation process.

To improve the performance of VEC specification in terms of these three points, Bollerslev, Engle, and Wooldridge (1988) introduce a simplified version of the VEC model. They assume that the parameter matrices A_i *and* B_j in the Equation 2.11 are diagonal matrices. With this diagonal VEC model the number of parameters decrease to $(p+q+1)N(N+1)/2$, therefore for the case of two, three and four series

there are 9,18 and 30 parameters to be estimated respectively[8], instead of 21,78 and 210. Diagonal form improves the parsimonious property. However original representation lose significant amount of flexibility and the interaction link among conditional variances and covariances of different series. Diagonal VEC specification also simplifies the derivation of conditions which ensures positive definiteness and it is possible to make H_t matrix positive definite for all t.

With diagonal parameter matrices it is possible to ensure positive definiteness of H_t by imposing necessary conditions but the model lose its flexibility. Engle and Kroner (1995) propose a new parametrization which guarantees the positive definiteness of H_t matrix by construction while preserving the flexibility.

2.3.1.2 BEKK-GARCH Model

Engle and Kroner (1995) define the Baba-Engle-Kraft-Kroner (BEKK) model with an attractive property that the conditional variance-covariance matrix is positive definite by construction. The BEKK-GARCH model has the form

$$H_t = CC' + \sum_{i=1}^{q}\sum_{k=1}^{K} A'_{ki} u_{t-i} u'_{t-i} A_{ki} + \sum_{j=1}^{p}\sum_{k=1}^{K} B'_{kj} H_{t-j} B_{kj} \tag{2.15}$$

where A, B,and C are $N \times N$ parameter matrices,and C is lower triangular.

For example, BEKK parametrization of bivariate GARCH(1,1) model (when $K = 1$) is

$$\begin{aligned} H_t &= \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{21} \\ 0 & c_{22} \end{bmatrix} \\ &+ \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} u^2_{1,t-1} & u_{1,t-1}u_{2,t-1} \\ u_{1,t-1}u_{2,t-1} & u^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{21} \\ b_{21} & b_{22} \end{bmatrix} \end{aligned} \tag{2.16}$$

where $h_{ii,t}$ and $h_{ij,t}$ correspond to variance of series i and covariance between series i and j respectively. Therefore similar to VEC parametrization, conditional variances

[8] If $p = q = 1$.

and covariance are defined as

$$
\begin{aligned}
h_{11,t} &= c_{11}^2 + a_{11}^2 u_{1,t-1}^2 + 2a_{11}a_{21}u_{1,t-1}u_{2,t-1} + a_{21}^2 u_{2,t-1}^2 \\
&\quad + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{21,t-1} + b_{21}^2 h_{22,t-1} \\
h_{21,t} &= c_{11}c_{21} + a_{11}a_{12}u_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})u_{1,t-1}u_{2,t-1} + a_{21}a_{22}u_{2,t-1}^2 \\
&\quad + b_{11}b_{12}h_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22})h_{21,t-1} + b_{21}b_{22}h_{22,t-1} \\
h_{22,t} &= (c_{21}^2 + c_{22}^2) + a_{12}^2 u_{1,t-1}^2 + 2a_{12}a_{22}u_{1,t-1}u_{2,t-1} + a_{22}^2 u_{2,t-1}^2 \\
&\quad + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{21,t-1} + b_{22}^2 h_{22,t-1}
\end{aligned}
\tag{2.17}
$$

which are functions of lagged squared errors of each series, cross product of lagged errors of each series, lagged conditional variance of each series and covariances between series with restricted parameters relative to VEC-GARCH model. The Equation 2.17 indicates that the effect of lagged errors on two variance and one covariance are represented by four elements of matrix A i.e. the *nine* parameters of VEC-GARCH model are represented by $four$ elements in BEKK-GARCH model. The same argument is valid for the effect of lagged conditional variance and covariance. Thus BEKK-GARCH model can be thought as a restricted version of VEC-GARCH model. When K is increased to *two* then the same *nine* parameters of VEC-GARCH model are represented by *eight* elements. Therefore the K represent the generality of the model and higher values of K makes the model more flexible. But at the same time the number of parameters to be estimated increase rapidly and reduce the parsimony of the model. There are $(p+q)KN^2 + N(N+1)/2$ parameters in conditional variance covariance matrix in its general form. However, in application it is generally assumed that $K = 1$ and GARCH(1,1) is sufficient. Then total number of parameters for the case of two series, three series and four series will be 11, 24 and 42 respectively. With respect to number of parameters the BEKK-GARCH model is preferable to VEC-GARCH model.

In terms of parsimonious property and the preserved positive definiteness by construction, the BEKK-GARCH model is preferable to VEC-GARCH model. However, the most important disadvantage of BEKK-GARCH model is that parameters lose their straightforward interpretation and it is difficult to interpret these model parameters which is not the case in VEC-GARCH model. VEC-GARCH model parameters have straightforward interpretation as in the univariate GARCH parameters discussed in previous section.

2.3.2 Indirect H_t Modeling

Although the analysis with BEKK-GARCH model is easier due to the less number of parameters and preserved positive definiteness by construction, the estimation of parameters is a very difficult task to manage in both VEC and BEKK parametrization

of H_t matrix which obstruct the widespread usage of these MGARCH models. The main reason of this is the inversion of H_t matrix for all t in each iteration. If the estimation procedure needs large number of iteration which is generally the case with a lot of parameters to be estimated then things become much more complicated. Bollerslev (1990) indicates that the estimation procedure of MGARCH models is significantly simplified if conditional covariance is modelled as a product of a constant conditional correlation and square root of variances instead of straightforward modeling of the conditional covariance. In this framework, increasing number of parameter and positive definite variance covariance matrix problems are easier to deal with relative to direct conditional covariance modeling.

2.3.2.1 CCC-GARCH Model

Bollerslev (1990) introduces a new class of MGARCH model called constant conditional correlation (CCC) model. In this model, dynamics for conditional covariances are defined implicitly as product of conditional correlation with square root of variances i.e. $h_{ij} = \rho_{ij}\sqrt{h_{ii}h_{jj}}$. He assumes that the conditional correlation is constant over time and time varying structure of conditional covariance comes from the time varying structure of conditional variance. Then, the H_t becomes

$$H_t = \begin{bmatrix} h_{11,t} & \rho_{12}\sqrt{h_{11,t}h_{22,t}} & \dots & \rho_{1N}\sqrt{h_{11,t}h_{NN,t}} \\ \rho_{21}\sqrt{h_{22,t}h_{11,t}} & h_{22,t} & \dots & \rho_{2N}\sqrt{h_{22,t}h_{NN,t}} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{N1}\sqrt{h_{NN,t}h_{11,t}} & \rho_{N2}\sqrt{h_{NN,t}h_{22,t}} & \dots & h_{NN,t} \end{bmatrix}$$

While there are N conditional variance equations and $N(N-1)/2$ unique conditional covariance equations which makes $N(N+1)/2$ total equations defined in the direct H_t modeling, there are only N equations defined in the CCC-GARCH model.

Instead of defining dynamic for H_t matrix, Bollerslev decompose this matrix as

$$H_t = D_t R D_t \tag{2.18}$$

where R is an $N \times N$ symmetric conditional correlation matrix of errors, u_t, and at the same time it is conditional covariance matrix of standardized errors, ε_t ($\varepsilon_t = D_t^{-1}u_t$) whose diagonal elements are *unity* and off-diagonal elements are less than or equal to *unity* in absolute value ($[-1, 1]$) and D_t is an diagonal matrix whose diagonal elements are square root of conditional variance. Thus instead of defining dynamic for H_t matrix, the elements of D_t matrix are defined.

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 & ... & 0 \\ 0 & \sqrt{h_{22,t}} & ... & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & ... & \sqrt{h_{NN,t}} \end{bmatrix} R \begin{bmatrix} \sqrt{h_{11,t}} & 0 & ... & 0 \\ 0 & \sqrt{h_{22,t}} & ... & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & ... & \sqrt{h_{NN,t}} \end{bmatrix}$$

$$\text{where } R = \begin{bmatrix} 1 & \rho_{12} & ... & \rho_{1N} \\ \rho_{21} & 1 & ... & \rho_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{N1} & \rho_{N2} & ... & 1 \end{bmatrix}$$

$$H_t = \begin{bmatrix} h_{11,t} & \rho_{12}\sqrt{h_{11,t}h_{22,t}} & ... & \rho_{1N}\sqrt{h_{11,t}h_{NN,t}} \\ \rho_{21}\sqrt{h_{22,t}h_{11,t}} & h_{22,t} & ... & \rho_{2N}\sqrt{h_{22,t}h_{NN,t}} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{N1}\sqrt{h_{NN,t}h_{11,t}} & \rho_{N2}\sqrt{h_{NN,t}h_{22,t}} & ... & h_{NN,t} \end{bmatrix}$$

In this CCC-GARCH model, the conditional correlation, R, is assumed to be constant so there is no need to define dynamic for it and the model consists of $N(N-1)/2$ unique conditional correlation parameters to be estimated. The elements of D_t matrix are square root of time varying conditional variance of each series. Therefore the specification of CCC model consists of defining conditional variance of each series. The appealing feature of this new class model is that each conditional variance equation can be formulated separately and each one can follow different GARCH process. Therefore this new class of model have the flexibility of univariate GARCH modeling.

The H_t matrix is positive definite for all t if each of the N conditional variances satisfies the positive variance requirement of univariate GARCH process and R is positive definite. For this case of constant conditional correlations, maximum likelihood estimate of correlations matrix is equal to sample correlation matrix which is always positive definite. Therefore positive definite variance-covariance matrix requirement is much easier to be satisfied in CCC-GARCH model than other MGARCH models.

Bollerslev (1990) assumes that in his CCC-GARCH model each conditional variance follows GARCH(1,1) process. This is equivalent to diagonal assumption in VEC and BEKK specifications and there is no interaction among different variance equations. Jeantheau (1998) relaxes this assumption and formulates more general CCC specification. His model is known as extended CCC (ECCC-GARCH). He defines each variance as a function of lagged squared errors and lagged variance of all series.

Under the assumption of multivariate normality of u_t, the log-likelihood is

$$\sum_{t=1}^{T} \ell_t = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(|H_t|) - \frac{1}{2}\sum_{t=1}^{T} u_t' H_t^{-1} u_t \qquad (2.19)$$

substituting the Equation 2.18 in to Equation 2.19 makes the log-likelihood

$$\sum_{t=1}^{T} \ell_t = -\frac{TN}{2}\ln(2\pi) - \frac{T}{2}\ln|R| - \sum_{t=1}^{T}\ln|D_t| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t^{'}R^{-1}\varepsilon_t \tag{2.20}$$

where $\varepsilon_t = D_t^{-1}u_t$ is $N \times 1$ vector of standardized errors. Note that this likelihood function is equivalent to the likelihood function of normally distributed ε_t with time invariant variance-covariance matrix R and a Jacobian term arising from the transformation of u_t to ε_t. Since the loglikelihood in Equation 2.20 requires the inversion of time invariant matrix of R, the numerical optimization by iteration is easier than other MGARCH parametrizations.

However the constant conditional correlation assumption may not be realistic assumption and its validity is tested in the literature. As reported by Tse (2002) and Bera and Kim (2002) constant conditional correlation is not a valid assumption for financial assets, which means that conditional correlation have a dynamic structure. Therefore this dynamic structure has to be formulated together with the elements of D_t matrix.

2.3.2.2 DCC-GARCH Model

Engle (2002) suggests a new model, Dynamic Conditional Correlation (DCC) which incorporates dynamic structure of conditional correlation by formulating GARCH type dynamics for the conditional correlation. The specification of DCC-GARCH model consist of N conditional variance equations and *one* conditional correlation equation. The main goal of this model is to construct large scale conditional variance-covariance matrix so the correlation equation is defined with scalar parameter instead of parameter matrix to keep the number of parameters in the conditional correlation equation low. Thus, this formulation assumes that all conditional correlation among N series are governed by same parameters.

DCC-GARCH employs the same decomposition of Bollerslev (1990) with time varying conditional correlation.

$$H_t = D_t R_t D_t \tag{2.21}$$

In DCC-GARCH model, a dynamic for conditional correlation, R_t, is not directly defined. Instead, a dynamic series, Q_t is created and R_t is defined by Q_t in a manner which guarantees that R_t become a regular correlation matrix whose diagonal entries must be unity and off-diagonal elements must be less than or equal to unity in absolute value. A stationary and mean reverting GARCH(1,1) process is defined for Q_t with nonnegative a and b scalar parameters which satisfies $a + b < 1$.

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon_{t-1}^{'} + bQ_{t-1} \tag{2.22}$$

$$R_t = Q_t^{*^{-1}} Q_t \; Q_t^{*^{-1}} \tag{2.23}$$

where Q_t^* is a diagonal matrix whose diagonal entries are square root of the diagonal elements of Q_t, and $\bar{Q}$ is the unconditional variance-covariance matrix of the standardized errors.

$$Q_t = \begin{bmatrix} q_{11,t} & q_{12,t} & \cdots & q_{1N,t} \\ q_{21,t} & q_{22,t} & \cdots & q_{2N,t} \\ \vdots & \vdots & \vdots & \vdots \\ q_{N1,t} & q_{N2,t} & \cdots & q_{NN,t} \end{bmatrix} \text{ and } Q_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \sqrt{q_{NN,t}} \end{bmatrix}$$

Then a typical element of R_t, $\rho_{ij,t}$ is

$$\begin{aligned} \rho_{ij,t} &= \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \\ \rho_{ij,t} &= \frac{(1-a-b)\bar{q}_{ij} + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{ij,t-1}}{\sqrt{((1-a-b)\bar{q}_{ii} + a\varepsilon_{i,t-1}^2 + bq_{ii,t-1})}\sqrt{((1-a-b)\bar{q}_{jj} + a\varepsilon_{j,t-1}^2 + bq_{jj,t-1})}} \end{aligned}$$

Since the conditional correlation matrix of errors is the variance-covariance matrix of standardized errors, defining GARCH type dynamics for conditional correlation requires the use of standardized errors whose conditional covariance equation is defined in the conditional correlation equations. As an analogue to variance equation, covariance equation can be defined as a function of cross product of lagged standardized errors. However, as it is discussed in Section 2.2.1, lagged standardized errors are employed to represent the true causes of conditional correlation and to improve the model performance in describing the conditional correlation. By inserting the relevant variables into the correlation equation, the causes of correlation can be determined within this framework and if the true causes of correlation could be identified then the cross product of the lagged standardized errors became redundant. However, in application cross product of the first lag of standardized errors have become default variables without any search for appropriate explanatory variables of the conditional correlation equation.

As an analogue to CCC-GARCH model, the H_t matrix is positive definite for all t if each of the N conditional variances satisfies the positive variance requirement of univariate GARCH process and R_t is positive definite for all t. Thus, the sufficient condition for positive definite R_t matrix is nonnegative scalars a and b.

Under the assumption of multivariate normality of u_t, the loglikelihood is

$$\sum_{t=1}^{T} \ell_t = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln(|H_t|) - \frac{1}{2}\sum_{t=1}^{T} u_t' H_t^{-1} u_t \tag{2.24}$$

substitute the Equation 2.21 in to Equation 2.24 then the loglikelihood becomes

$$\sum_{t=1}^{T} \ell_t = -\frac{TN}{2}\ln(2\pi) - \frac{T}{2}\ln|R_t| - \sum_{t=1}^{T}\ln|D_t| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t' R_t^{-1}\varepsilon_t \tag{2.25}$$

Computational simplicity of CCC-GARCH model disappears under time varying conditional correlation matrix R_t. The loglikelihood in Equation 2.25 requires the inverse of this matrix for all t in each iteration. To this end, Engle (2002) introduces two step estimation and Engle et. al. (2001) and Engle (2002) indicate that model parameters can be estimated consistently with this two step estimation. Engle (2002) adds $u_t' D_t^{-1} D_t^{-1} u_t$ (which is equal to $\varepsilon_t'\varepsilon_t$) term to and subtracts $\varepsilon_t'\varepsilon_t$ term from the loglikelihood of each observation t, so the the likelihood becomes

$$\begin{aligned}\sum_{t=1}^{T} \ell_t &= -\frac{TN}{2}\ln(2\pi) - \frac{T}{2}\ln|R_t| - \sum_{t=1}^{T}\ln|D_t| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t' R_t^{-1}\varepsilon_t \\ &\quad - \sum_{t=1}^{T} u_t' D_t^{-1} D_t^{-1} u_t + \sum_{t=1}^{T}\varepsilon_t'\varepsilon_t \end{aligned} \tag{2.26}$$

$$\begin{aligned} &= \underbrace{[-\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\ln|D_t|^2 + u_t' D_t^{-2} u_t)]}_{(I)} \\ &\quad \underbrace{+[-\frac{1}{2}\sum_{t=1}^{T}(\ln|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t + \varepsilon_t'\varepsilon_t)]}_{(II)} \end{aligned}$$

where the part (I) corresponds to volatility term while the part (II) corresponds to correlation term. Since D_t is a diagonal matrix then $|D_t|$ is equal to product of the diagonal elements which are square root of conditional variance. Thus $\ln|D_t|^2$ term in the (I) part of the Equation 2.26 just equals to the summation of logarithm of conditional variances i.e. $\sum_i \ln(h_{ii,t})$ and $u_t' D_t^{-2} u_t$ term in this part equals to $\sum_i u_{i,t}^2/h_{ii,t}$. Thus the (I) part can be written as

$$(I) \Longrightarrow -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}[\ln(2\pi) + \ln(h_{ii,t}) + \frac{u_{i,t}^2}{h_{ii,t}}]$$

which is equal to summation of all univariate loglikelihood functions in the Equation 2.4. Therefore volatility part can be maximized by separately maximizing each univariate GARCH process of series.

Correlation parameters of the DCC-GARCH model can be estimated by maximizing

the part (II) of the Equation 2.26. Engle (2002) argues that the squared residuals are not dependent on correlation parameters, they will not enter the first order conditions and can be ignored. Thus the estimation procedure is as follows: first estimate separate univariate GARCH model for each series and calculate standardized error vector $\hat{\varepsilon}_t$. Secondly, estimate conditional correlation from maximizing the part (II) of the Equation 2.26 by using the $\hat{\varepsilon}_t$ from first step. However in this framework the potential link between variance and correlation equations are ignored and there is no interaction between individual GARCH processes and correlation process.

With this two step estimation, large system can be estimated consistently. However the scalar parameters in the conditional correlation equation which assumes that all correlations are govern by same parameters become unrealistic for a large system. One obvious solution is to replace scalar parameters with matrices but this increase the number of parameters very quickly as dimension of N increases and estimation requires more iteration and may become unstable.

2.3.2.3 STCC-GARCH Model

Motivated from the observation that the correlation among assets and markets are higher during the turbulence period than they are during more calm periods, Silvennoinen and Teräsvirta (2005) introduce the smooth transition conditional correlation (STCC-GARCH) model. They define two extreme regimes characterized by specific constant conditional correlations; one for, for example, turbulence period and one for calm period. The conditional correlation varies smoothly between these two extremes as a function of a transition variable. Following Bollerslev (1990), Silvennoinen and Teräsvirta decompose conditional variance-covariance matrix, H_t as

$$H_t = D_t R_t D_t \tag{2.27}$$

Therefore, as in CCC and DCC specifications, separate univariate variances are defined for N series and each one can follow different GARCH process. STCC-GARCH model formulates the time varying conditional correlation matrix, R_t as a function of two regime specific constant conditional correlation matrices.

$$R_t = P_1(1 - G_t(s_t;\varphi)) + P_2 G_t(s_t;\varphi) \tag{2.28}$$

where P_1 and P_2 are distinct and positive definite regime specific constant correlation matrices whose diagonal entries must be unity and off-diagonal elements must be less than or equal to unity in absolute value as in regular correlation matrix. However unlike DCC-GARCH model of Engle (2002), this is not guaranteed by construction. Since the off-diagonal elements of P_1 and P_2 are parameters to be estimated, this should be controlled during the estimation.

The typical element of R_t in this framework is $\rho_{ij,t}$

$$\rho_{ij,t} = \rho_{1ij}(1 - G_t(s_t;\varphi)) + \rho_{2ij}G_t(s_t;\varphi)$$

where ρ_{1ij} and ρ_{2ij} are the elements of P_1 and P_2 respectively and regime specific constant correlations between series i and j.

In equation 2.28, $G_t(s_t;\varphi)$ is a transition function which is assumed to be continuous and bounded between *zero* and *unity*. It is defined as a function of an observable transition variable, s_t, with parameter space φ. If $G_t = 0$ then the conditional correlation is governed by only P_1 and it is said that the conditional correlation is in the first regime with respect to transition variable, s_t. On the other hand, when $G_t = 1$ then the correlation is said to be in second regime with respect to transition variable, s_t and the conditional correlation is equal to P_2. The other values of the transition function (i.e. $G_t \in (0, 1)$) corresponds to transition between extreme regimes and during transition the conditional correlation, R_t, is a convex combination of P_1 and P_2.

The proper choice of transition function is the logistic one

$$G_t = (1 + e^{-\gamma(s_t - c)})^{-1} \quad \gamma > 0 \tag{2.29}$$

The transition function represented by logistic function is monotonically increasing from *zero* to *one* depending on the value of transition variable s_t. This function is characterized by parameters γ and c (thus $\varphi = (\gamma, c)$). The former one is the slope of the function determining the smoothness of the transition from one regime to other regime. Figure 2.2 presents typical shape of a logistic function for various values of γ and as its magnitude increases the transition becomes sharper. Therefore STCC-GARCH model nests the TAR model which defines step function: the transition occurs very sharply. The latter parameter is the threshold value denoting the half-way point between these two regimes. When s_t is lower than the threshold value, c, the transition function, G_t takes values less than 0.5 and goes to *zero* as s_t decreases so P_1 describes the conditional correlation. Similarly when s_t rises above the threshold value, G_t becomes higher than 0.5 and goes to *unity* making P_2 dominant. Therefore STCC-GARCH model describes a monotonic transition from P_1 to P_2 as s_t increases for the conditional correlation, R_t.

The STCC framework of Silvennoinen and Teräsvirta has three important advantages over DCC specification. First of all, the model is capable of incorporating the possibility of heterogeneous agents which may responds to developments at different values of transition variable by defining smooth transition between extreme regimes. The second advantage is the flexibility of STCC-GARCH model with respect to explanatory variables in the conditional correlation equation. In DCC-GARCH mod-

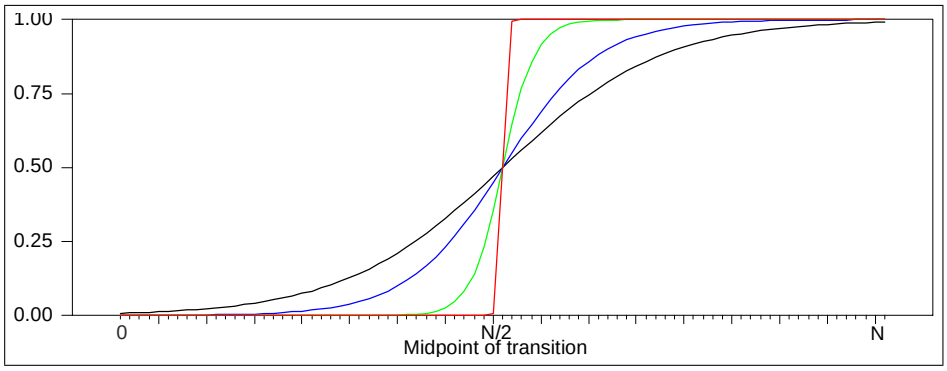


Figure 2.2: Logistic function for various values of γ

eling, the first lag of standardized errors are used as default explanatory variable in the correlation equation without any search procedure for appropriate explanatory variables and if the lagged standardized errors are not sufficient to represent the factors which are responsible for time varying structure of conditional correlation then the DCC specification cannot successfully capture the dynamics of conditional correlation. On the other hand, in STCC-GARCH model, time varying structure of conditional correlation can be a function of any observable variable, or combination of observable variables. The choice of transition variable is very crucial and the performance of the STCC-GARCH model depends on the ability of transition variable in representing the factors which determine the time varying nature of the conditional correlation. Transition variable is chosen according to the purpose of the application. For example, if the purpose of the application is to search for an evidence of increasing trend in conditional correlations among financial markets, then the suitable transition variable will be calendar time. The usage of time variable gives rise to the time-varying conditional correlations model of Berben and Jansen (2005) which is a special case of the STCC-GARCH model allowing a smooth change between correlation regimes and as $\gamma \to \infty$ captures a structural break in the correlations. If the purpose is to examine the validity of argument that correlations among international markets become very high during global crisis and return to low levels during calm periods then the choice of transition variable will be a measure of global market risk such as VIX[9] index. Similarly, the effects of business cycles on the conditional correlation can be investigated in the STCC context by choosing a measure of business cycle as a transition variable. Therefore the STCC-GARCH model is very flexible in determining and testing various factors which affect the conditional correlation. In line with the aim of this thesis, STCC and its extension DSTCC specifications not only can characterize increasing trend by using calendar time as transition variable but also are able to uncover the structure and properties

[9]The Chicago Board Options Exchange volatility index, VIX, is constructed using the implied volatilities of a wide range of S&P 500 index options.

of correlation in response to global volatility, market specific volatility and news from markets, and hence these models are preferred in this thesis. Finally, STCC procedure result in more realistic and efficient estimates. Unlike two step estimation in DCC-GARCH model, the estimation of STCC-GARCH takes the interaction between individual GARCH processes and correlation process in to consideration. Thus, it is expected that STCC estimates are more realistic and efficient than DCC-GARCH model estimation.

The conditional correlation matrix, R_t is always positive definite in STCC-GARCH model because it is a linear combination of two positive definite constant correlation matrix. Therefore the conditional variance-covariance matrix, H_t is positive definite for all t if each of the N conditional variance satisfies the positive variance requirement of univariate GARCH process.

Silvennoinen and Teräsvirta (2005) employ maximum likelihood (ML) under the assumption of conditional normality of standardized errors[10] to estimate STCC-GARCH model.

$$\sum_{t=1}^{T} \ell_t = -\frac{TN}{2}\ln(2\pi) - \frac{T}{2}\ln|R_t| - \sum_{t=1}^{T}\ln|D_t| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t' R_t^{-1}\varepsilon_t \tag{2.30}$$

Due to nonlinear fashion of the model and the large number of parameters in the model, it is very difficult to estimate all equations (mean, variance, correlation and transition function) jointly at once. Therefore the iterative procedure suggested by Silvennoinen and Teräsvirta (2005) is used. This procedure divides the parameters into three sets: parameters in the mean and variance equations, parameters in the correlations, and parameters of the transition function. Then the log-likelihood is maximized by sequential iteration over each set by holding the parameters of other sets at their previously estimated values. Initial values of parameters are very crucial in estimation and different initial values may lead to convergence to different parameter values corresponding to local maxima. As an attempt to attain the global maximum, grid search has to be performed over the parameters of the transition function. The parameter values which generate the maximum likelihood value should be chosen and with these initial values, all equations are estimated simultaneously at once.

Before estimating the STCC-GARCH model with particular transition variable it is necessary to test the null hypothesis that conditional correlation is constant with respect to this particular transition variable. If the true conditional correlation process is constant with respect to the transition variable then the STCC specification has an identification problem which yields inconsistent parameter estimates. Silvennoinen

[10] The log-likelihood will be same under the assumption of normal errors: $u_t|\Psi_t \sim N(0, H_t)$.

and Teräsvirta (2005) suggest a Lagrange multiplier (LM_1) test for this purposes which is explained in Section 2.3.3. The conventional smooth transition modeling[11] suggests that the variable which most significantly rejects the null hypothesis of constant conditional correlation should be chosen as a transition variable among all candidate transition variables.

Generally in applications, when the time horizon of the model is long, the calendar time is the variable which rejects the null hypothesis of constant conditional correlation most significantly. To further improve the model fit and to be able to test various variables' effect on the conditional correlation Silvennoinen and Teräsvirta (2009) extend the STCC-GARCH model to double smooth transition variable (DSTCC) model allowing two transition variables in the conditional correlation equation.

2.3.2.4 DSTCC-GARCH Model

Silvennoinen and Teräsvirta (2009) generalize the Equation 2.28 to allow for two transition functions with two transition variables by relaxing the assumption that P_1 and P_2 are regime specific constant correlations and define $P_{1,t}$ and $P_{2,t}$. In DSTCC-GARCH model, conditional correlation, R_t, takes values between $P_{1,t}$ and $P_{2,t}$ as a function of the first transition function with respect to the first observable transition variable.

$$R_t = P_{1,t}(1 - G_{1,t}(s_{1,t}; \gamma_1, c_1)) + P_{2,t}G_{1,t}(s_{1,t}; \gamma_1, c_1) \tag{2.31}$$

As a function of the second transition function with respect to observable second transition variable, $P_{1,t}$ and $P_{2,t}$ take values between P_{11} and P_{12}, and P_{21} and P_{22} respectively.

$$P_{m,t} = P_{m1}(1 - G_{2,t}(s_{2,t}; \gamma_2, c_2)) + P_{m2}G_{2,t}(s_{2,t}; \gamma_2, c_2) \quad m = 1, 2 \tag{2.32}$$

If the transition variables are same then conditional correlation is governed by three extreme regime specific correlations with two distinct transition functions and if they are different it is governed by four extreme regime specific correlations with two distinct transition functions. When Equation 2.32 is substituted in to Equation 2.31, the conditional correlation equation becomes

$$R_t = (1 - G_{2,t})[(1 - G_{1,t})P_{11} + G_{1,t}P_{21}] + G_{2,t}[(1 - G_{1,t})P_{12} + G_{1,t}P_{22}] \tag{2.33}$$

where the transition functions $G_{1,t}(s_{1,t}; \gamma_1, c_1)$ and $G_{2,t}(s_{2,t}; \gamma_2, c_2)$ are logistic functions with distinct transition variables ($s_{1,t}$ *and* $s_{2,t}$), different locations (c_1 *and* c_2)

[11] See Teräsvirta and Anderson (1992), Teräsvirta (1995), and Dijk, Terasvirta and Franses (2002).

and different speed of adjustments (γ_1 *and* γ_2). P_{11}, P_{12}, P_{21} and P_{22} are regime specific constant correlations matrices. To be clearer, the first transition function describes two different regimes (P_1 and P_2) and the second one allows two distinct regimes within the each regime of the former one (i.e. $P_1 \rightarrow P_{11}$ and P_{12} ; $P_2 \rightarrow P_{21}$ and P_{22}). When the conditional correlation is in the first regime with respect to the second transition function (i.e. $G_{2,t} = 0$), R_t takes on values between P_{11} and P_{21} as a function of the first transition function, and during the second regime (when $G_{2,t} = 1$) it takes on values between P_{12} and P_{22} as a function of the first transition function. Hence, the system can move from P_{11} to P_{21} and P_{12} to P_{22} only by the dynamics of the first transition function in case of these extremes. Otherwise, the movements among four regimes[12] are governed by both transition functions.

2.3.3 Testing Constant Conditional Correlation Assumption

Constant conditional correlation assumption of Bollerslev (1990) considerably simplifies the estimation procedure of MGARCH. Thus it is not logical to intend to start difficult task of estimating time varying conditional correlation models unless one is sure that the constant correlation assumption fails to hold. In addition, the parameter estimates of STCC specification may be inconsistent if the true model has constant conditional correlation. Therefore before estimating time varying conditional correlation model, the constant conditional correlation hypothesis should be tested. There are various test procedures suggested in the literature. In this section, Lagrange multiplier (LM) test of Tse (2002), constant correlation test of Silvennoinen and Teräsvirta (2005) and additional transition test of Silvennoinen and Teräsvirta (2009) are discussed.

2.3.3.1 Testing against General Time Varying Conditional Correlation

Tse (2002) generalizes the CCC-GARCH model of Bollerslev(1990) by defining time varying structure for each element of conditional correlation matrix, R_t as follows;

$$\begin{aligned} h_{ii,t} &= \alpha_{0,i} + \alpha_{1,i} u_{i,t-1}^2 + \beta_{1,i} h_{ii,t-1} \\ h_{ij,t} &= \rho_{ij,t} \sqrt{h_{ii,t} h_{jj,t}} \\ \rho_{ij,t} &= \rho_{ij} + \delta_{ij} u_{i,t-1} u_{j,t-1} \end{aligned} \tag{2.34}$$

then the null hypothesis is $H_0 : \delta_{ij} = 0$ for all ij such that $i \neq j$. Therefore there are $N(N-1)/2$ restrictions. The model under null hypothesis is CCC-GARCH model of Bollerslev (1990), so Tse (2002) employs Lagrange multiplier (LM) test which requires only the estimation of restricted model of CCC-GARCH which is very easy to estimate.

[12] If the transition variables are the same then conditional correlation is governed by three extreme regime specific correlations with two distinct transition functions, See Öcal and Osborn (2000).

Under the assumption of multivariate normality of u_t, the contribution of t^{th} observations to the loglikelihood is

$$\ell_t = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|R_t| - \frac{1}{2}\ln|D_t^2| - \frac{1}{2}u_t' H_t^{-1} u_t$$

The derivative of this function with respect to intercept term in the variance equation of series i;

$$\begin{aligned}\frac{\partial \ell_t}{\partial \alpha_{0,i}} &= -\frac{1}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial \alpha_{0,i}} - \\ &\quad \frac{1}{2}\underbrace{\frac{\partial (vec(D_t^{-1}))'}{\partial h_{ii,t}}}_{(3)}\underbrace{\frac{\partial (vec(H_t^{-1}))'}{\partial vec(D_t^{-1})}}_{(2)}\underbrace{\frac{\partial u_t' H_t^{-1} u_t}{\partial vec(H_t^{-1})}}_{(1)}\frac{\partial h_{ii,t}}{\partial \alpha_{0,i}}\end{aligned} \tag{2.35}$$

the term (1) is equal to

$$\begin{aligned}(1) \implies \frac{\partial u_t' H_t^{-1} u_t}{\partial vec(H_t^{-1})} &= vec(\frac{\partial u_t' H_t^{-1} u_t}{\partial H_t^{-1}}) \quad \text{(see Lütkepohl p.176 (7))} \\ &= vec(u_t u_t') \quad \text{(see Lütkepohl p.177 (8))} \\ &= (u_t \otimes u_t) \quad \text{(see Lütkepohl p.20 (13))}\end{aligned}$$

the term (2) is equal to

$$\begin{aligned}(2) \implies \frac{\partial (vec(H_t^{-1}))'}{\partial vec(D_t^{-1})} &= \frac{\partial (vec(D_t^{-1}R_t^{-1}D_t^{-1}))'}{\partial vec(D_t^{-1})} \\ &= (D_t^{-1}R_t^{-1} \otimes I_N + I_N \otimes D_t^{-1}R_t^{-1})' \quad \text{(see Lütkepohl p.190 (3))} \\ &= (D_t^{-1}R_t^{-1} \otimes I_N)' + (I_N \otimes D_t^{-1}R_t^{-1})' \quad \text{(see Lütkepohl p.23 (11))} \\ &= [(D_t^{-1}R_t^{-1})' \otimes (I_N)'] + [(I_N)' \otimes (D_t^{-1}R_t^{-1})'] \quad \text{(see Lütkepohl p.23 (4))} \\ &= [(R_t^{-1}D_t^{-1} \otimes I_N) + (I_N \otimes R_t^{-1}D_t^{-1})] \quad \text{(see Lütkepohl p.23 (3))}\end{aligned}$$

the term (3) is equal to

$$(3) \implies \frac{\partial (vec(D_t^{-1}))'}{\partial h_{ii,t}} = -[M_i^N]'\frac{1}{2h_{ii,t}\sqrt{h_{ii,t}}}$$

where M_i^N is a $N^2 \times 1$ column vector whose i^2 element is 1 and other elements are 0. For example,

$$[M_2^3]' = \begin{bmatrix}0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0\end{bmatrix}$$

The product of (2)(1) is equal to

$$
\begin{aligned}
(2)(1) &= [(R_t^{-1}D_t^{-1} \otimes I_N) + (I_N \otimes R_t^{-1}D_t^{-1})](u_t \otimes u_t) \\
&= (R_t^{-1}D_t^{-1} \otimes I_N)(u_t \otimes u_t) + (I_N \otimes R_t^{-1}D_t^{-1})(u_t \otimes u_t) \quad \text{(see p.16 (4))} \\
&= (R_t^{-1}\varepsilon_t \otimes u_t) + (u_t \otimes R_t^{-1}\varepsilon_t) \qquad \text{(see Lütkepohl p.19 (5))} \\
&= (v_t \otimes u_t) + (u_t \otimes v_t)
\end{aligned}
$$

where $v_t = R_t^{-1}\varepsilon_t$. When the product of (2)(1) is multiplied by (3)

$$
\begin{aligned}
(3)(2)(1) &= -\frac{1}{2h_{ii,t}\sqrt{h_{ii,t}}}[M_i^N]'[(v_t \otimes u_t) + (u_t \otimes v_t)] \\
&= -\frac{1}{h_{ii,t}}v_{i,t}\varepsilon_{i,t}
\end{aligned}
$$

finally, substitute this product in to Equation 2.35

$$
\frac{\partial \ell_t}{\partial \alpha_{0,i}} = \frac{(v_{i,t}\varepsilon_{i,t} - 1)}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial \alpha_{0,i}}
$$

The derivative of loglikelihood with respect to $\alpha_{1,i}$ parameter in the variance equation of series i;

$$
\begin{aligned}
\frac{\partial \ell_t}{\partial \alpha_{1,i}} &= -\frac{1}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial \alpha_{1,i}} - \\
&\frac{1}{2}\underbrace{\frac{\partial (vec(D_t^{-1}))'}{\partial h_{ii,t}}}_{(3)}\underbrace{\frac{\partial (vec(H_t^{-1}))'}{\partial vec(D_t^{-1})}}_{(2)}\underbrace{\frac{\partial u_t' H_t^{-1} u_t}{\partial vec(H_t^{-1})}}_{(1)}\frac{\partial h_{ii,t}}{\partial \alpha_{1,i}}
\end{aligned} \tag{2.36}
$$

the terms $(1), (2)$ and (3) are same as the previous ones, so the product of these terms is

$$
\begin{aligned}
(3)(2)(1) &= -\frac{1}{2h_{ii,t}\sqrt{h_{ii,t}}}[M_i^N]'[(v_t \otimes \varepsilon_t) + (\varepsilon_t \otimes v_t)] \\
&= \frac{1}{2h_{ii,t}}v_{i,t}\varepsilon_{i,t}
\end{aligned}
$$

substituting this product in to Equation 2.36 delivers

$$
\frac{\partial \ell_t}{\partial \alpha_{1,i}} = \frac{(v_{i,t}\varepsilon_{i,t} - 1)}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial \alpha_{1,i}}
$$

As an analogue to previous derivatives, the derivative of loglikelihood with respect to $\beta_{1,i}$ parameter in the variance equation of series i is equal to

$$
\frac{\partial \ell_t}{\partial \beta_{1,i}} = \frac{(v_{i,t}\varepsilon_{i,t} - 1)}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial \beta_{1,i}}
$$

The derivatives of $\frac{\partial h_{ii,t}}{\partial \alpha_{0,i}}$, $\frac{\partial h_{ii,t}}{\partial \alpha_{1,i}}$ and $\frac{\partial h_{ii,t}}{\partial \beta_{1,i}}$ requires recursive derivatives: i.e.

$$\begin{aligned}
\frac{\partial h_{ii,t}}{\partial \alpha_{0,i}} &= 1 + \beta_1 \frac{\partial h_{ii,t-1}}{\partial \alpha_{0,i}} \\
\frac{\partial h_{ii,t}}{\partial \alpha_{1,i}} &= u_{i,t-1}^2 + \beta_1 \frac{\partial h_{ii,t-1}}{\partial \alpha_{1,i}} \\
\frac{\partial h_{ii,t}}{\partial \beta_{1,i}} &= h_{ii,t-1} + \beta_1 \frac{\partial h_{ii,t-1}}{\partial \beta_{1,i}}
\end{aligned}$$

The derivative of loglikelihood with respect to ρ_{ij} parameter in the correlation equation

$$\begin{aligned}
\frac{\partial \ell_t}{\partial \rho_{ij}} &= -\frac{1}{2} \underbrace{\frac{\partial \rho_{ij,t}}{\partial \rho_{ij}}}_{(1)} \underbrace{\frac{\partial (vecR_t)'}{\partial \rho_{ij,t}}}_{(2)} \underbrace{\frac{\partial (\ln |R_t|)}{\partial (vecR_t)}}_{(3)} \\
&\quad -\frac{1}{2} \underbrace{\frac{\partial \rho_{ij,t}}{\partial \rho_{ij}}}_{(1)} \underbrace{\frac{\partial (vecR_t)'}{\partial \rho_{ij,t}}}_{(2)} \underbrace{\frac{\partial (vecR_t^{-1})'}{\partial (vecR_t)}}_{(4)} \underbrace{\frac{\partial \varepsilon_t' R_t^{-1} \varepsilon_t}{\partial (vecR_t^{-1})}}_{(5)}
\end{aligned} \tag{2.37}$$

the term (1) is equal to

$$(1) \Longrightarrow \frac{\partial \rho_{ij,t}}{\partial \rho_{ij}} = \frac{\partial (\rho_{ij} + \delta_{ij} u_{i,t-1} u_{j,t-1})}{\partial \rho_{ij}} = 1$$

the term (2) is equal to

$$(2) \Longrightarrow \frac{\partial (vecR_t)'}{\partial \rho_{ij,t}} = [F_{ij}^N]'$$

where F_{ij}^N is an $N^2 \times 1$ column vector whose $(j-1)N + i$ and $(i-1)N + j$ elements are 1, other elements are 0, for example if $N = 3$ then $[F_{21,3}]'$ and $[F_{13,3}]'$ equal to

$$\begin{aligned}
[F_{21}^3]' &= \begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{and} \\
[F_{13}^3]' &= \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}
\end{aligned}$$

the term (3) is equal to

$$\begin{aligned}
(3) \quad \Longrightarrow \quad & \frac{\partial (\ln |R_t|)}{\partial (vecR_t)} = vec(\frac{\partial (\ln |R_t|)}{\partial R_t}) \\
= \quad & vecR_t^{-1} \quad \text{(see Lütkepohl p.182 (10))}
\end{aligned}$$

the term (4) is equal to

$$(4) \Longrightarrow \frac{\partial (vecR_t^{-1})'}{\partial (vecR_t)} = -(R_t^{-1} \otimes R_t^{-1})' \quad \text{(see Lütkepohl p.198 (1))}$$

the term (5) is equal to

$$\begin{aligned}(5) \implies & \frac{\partial \varepsilon_t' R_t^{-1} \varepsilon_t}{\partial (vec R_t^{-1})} = vec(\frac{\partial \varepsilon_t' R_t^{-1} \varepsilon_t}{\partial R_t^{-1}}) = vec(\varepsilon_t \varepsilon_t') \\ = & (\varepsilon_t \otimes \varepsilon_t)\end{aligned}$$

the product of terms (1)(2)(3) equals to

$$(1)(2)(3) = [F_{ij,N}]' vec R_t^{-1} = 2\rho_t^{ij}$$

where ρ_t^{ij} is the ij^{th} element of inverse of conditional correlation matrix and the product of (1)(2)(4)(5) equals to

$$\begin{aligned}(1)(2)(4)(5) &= -[F_{ij,N}]'(R_t^{-1} \otimes R_t^{-1})'(\varepsilon_t \otimes \varepsilon_t) \\ &= -[F_{ij,N}]'(R_t^{-1} \otimes R_t^{-1})(\varepsilon_t \otimes \varepsilon_t) \\ &= -[F_{ij,N}]'(R_t^{-1}\varepsilon_t \otimes R_t^{-1}\varepsilon_t) \\ &= -[F_{ij,N}]' vec(v_t v_t') \\ &= -2 v_{i,t} v_{j,t}\end{aligned}$$

finally, substitute these product in to Equation 2.37

$$\frac{\partial \ell_t}{\partial \rho_{ij}} = (v_{i,t} v_{j,t} - \rho_t^{ij})$$

The derivative of loglikelihood with respect to δ_{ij} parameter in the correlation equation

$$\begin{aligned}\frac{\partial \ell_t}{\partial \delta_{ij}} = & -\frac{1}{2} \underbrace{\frac{\partial \rho_{ij,t}}{\partial \delta_{ij}}}_{(1)} \underbrace{\frac{\partial (vec R_t)'}{\partial \rho_{ij,t}}}_{(2)} \underbrace{\frac{\partial (\ln |R_t|)}{\partial (vec R_t)}}_{(3)} \\ & -\frac{1}{2} \underbrace{\frac{\partial \rho_{ij,t}}{\partial \delta_{ij}}}_{(1)} \underbrace{\frac{\partial (vec R_t)'}{\partial \rho_{ij,t}}}_{(2)} \underbrace{\frac{\partial (vec R_t^{-1})'}{\partial (vec R_t)}}_{(4)} \underbrace{\frac{\partial \varepsilon_t' R_t^{-1} \varepsilon_t}{\partial (vec R_t^{-1})}}_{(5)}\end{aligned} \tag{2.38}$$

the term (1) is equal to

$$(1) \Longrightarrow \frac{\partial \rho_{ij,t}}{\partial \delta_{ij}} = \frac{\partial (\rho_{ij} + \delta_{ij} u_{i,t-1} u_{j,t-1})}{\partial \delta_{ij}} = u_{i,t-1} u_{j,t-1}$$

the terms $(2), (3), (4)$ and (5) are identical to previous ones, thus

$$\frac{\partial \ell_t}{\partial \delta_{ij}} = (v_{i,t} v_{j,t} - \rho_t^{ij}) u_{i,t-1} u_{j,t-1}$$

The LM test statistic is derived from restricted model, and with constant conditional

correlation restriction the ρ_t^{ij} term reduces to time invariant conditional correlation ρ^{ij}. Thus the standardized errors, ε_t are from restricted model which is CCC in this case and v_t series are created by dividing ε_t to a constant ρ^{ij}. The usual LM statistics is

$$LM = (\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}'})[I(\hat{\theta})]^{-1}(\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}})$$

where θ is the parameter vector which consists of K parameters which is equal to $N^2 + 2N$ ($3N$ variance parameters and $N(N-1)$ correlation parameters) and $I(\hat{\theta})$ is the information matrix. The LM statistics is evaluated by restricted parameters which means that the parameters from CCC model are used. The definition of information matrix is

$$\sum_{t=1}^{T} E[\frac{\partial \ell_t}{\partial \theta} \frac{\partial \ell_t}{\partial \theta'}]$$

where definition requires taking expectation. Instead, if this theoretical estimator is replaced with outer product of gradients (OPG) to estimate second derivatives matrix, Hessian, the LM statistics become very easy to compute. Define G as a $T \times K$ matrix and each column corresponds to derivative of loglikelihood with respect to variance and correlation parameters; $\partial \ell_t / \partial \theta$.By OPG estimator, information matrix can be represented by sum of product of the first derivatives of ℓ_t. Thus the inverse of information matrix is

$$[I(\hat{\theta})]^{-1} = [G'G]^{-1}$$

and the score vector, $\sum \partial \ell_t / \partial \hat{\theta}$ can be expressed with G as $G'1_T$. Then the LM statistics become

$$\begin{aligned} LM &= (\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}'})[I(\hat{\theta})]^{-1}(\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}}) \\ &= 1_T G(G'G)^{-1}G'1_T \end{aligned}$$

It can be showed that this form of LM statistics is the product of T, sample size, and the R^2, uncentered squared multiple correlation coefficient, from a linear regression of $1s$ on the derivatives of the log-likelihood function computed at the restricted estimator (Greene,2004). It is argued that this form of LM-statistics tends to be less reliable in finite samples (Davidson and MacKinnon, 2002). However the sample size in financial application is generally very high so the results are reliable.

2.3.3.2 Testing against STCC-GARCH Model

The model proposed by Silvennoinen and Teräsvirta (2005) consists of mean, variance and correlation equations.

$$\text{Mean Eq:} \quad y_t = \mu_t + u_t$$

$$u_t|\Psi_t \sim (0, H_t)$$

where μ_t is conditional mean vector of series. It can be a function of exogenous and lagged endogenous variables with different parameters for each series.

$$\text{Variance Eq:} \quad H_t = D_t R_t D_t$$

$$h_{ii,t} = \alpha_{i0} + \alpha_{i1} u^2_{i,t-1} + \beta_{i1} h_{ii,t-1}$$

where variance-covariance matrix is decomposed following Bollerslev and each variance is modeled separately and can attain different process. Conditional correlation is defined as a linear combination of two constant extreme correlations as follows;

$$\text{Correlation Eq:} \ R_t = P_1(1 - G_t(s_t;\gamma,c)) + P_2 G_t(s_t;\gamma,c)$$

$$G_t = (1 + e^{-\gamma(s_t - c)})^{-1} \qquad \gamma > 0$$

The CCC-GARCH model is nested in the STCC-GARCH model and this specification provides a straightforward test procedure. Since the restricted model is very easy to estimate relative to unrestricted STCC-GARCH model, like Tse (2002), Silvennoinen and Teräsvirta (2005) suggest a LM type test.

If the restriction $\gamma = 0$ is imposed, the STCC-GARCH model becomes CCC-GARCH with constant conditional correlation of $(P_1 + P_2)/2$. Thus the null hypothesis is H_0: $\gamma = 0$ against STCC-GARCH model. However the rejection of this null hypothesis only suggests that the conditional correlation is not constant, i.e. it is time varying but not necessarily means that it has STCC type.

To avoid identification problem when $\gamma = 0$, Luukkonen et. al.(1988) introduce an auxiliary null hypothesis to approximate the null by using first order Taylor series approximation to logistic transition function around the true null.

$$\begin{aligned}
G_t &\simeq G_t|_{\gamma=0} + \nabla G_t|_{\gamma=0}(\gamma - 0) \\
&\simeq 1/2 + \{[-(1 + e^{-\gamma(s_t-c)})^{-2}(-(s_t - c)e^{-\gamma(s_t-c)})]_{\gamma=0}\}(\gamma) \\
&\simeq 1/2 + 1/4(s_t - c)\gamma
\end{aligned}$$

Substituting this approximation in to correlation equation results in

$$\begin{aligned}
R_t &\simeq P_1(1 - (1/2 + 1/4(s_t - c)\gamma)) + P_2(1/2 + 1/4(s_t - c)\gamma) \\
R_t &\simeq P_1(1/2 - 1/4(s_t - c)\gamma) + P_2(1/2 + 1/4(s_t - c)\gamma) \\
&\simeq \underbrace{[\frac{P_1 + P_2}{2} + \frac{\gamma c(P_1 - P_2)}{4}]}_{P_1^*} - \underbrace{[\frac{\gamma(P_1 - P_2)}{4}]}_{P_2^*} s_t \\
&\simeq P_1^* - P_2^* s_t
\end{aligned}$$

if $\gamma = 0$ then $P_2^* = 0$ and the conditional correlation becomes constant $((P_1+P_2)/2)$. Since the interest is in the unique off-diagonal elements of P_2^* the auxiliary null hypothesis restricts these unique off-diagonals to be 0. Thus $H_0 : vecl P_2^* = 0$. The vecl operator stacks the columns of the lower diagonal without diagonal elements of the square matrix as follows;

$$\text{If } P = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \text{ then } vecl(P) = \begin{bmatrix} p_{21} \\ p_{31} \\ p_{32} \end{bmatrix}$$

Instead of using the simple OPG form, Silvennoinen and Teräsvirta (2005) calculate the inverse of information matrix through regular definition of information matrix; i.e.

$$\begin{aligned} LM_1 &= (\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}'})[I(\hat{\theta})]^{-1}(\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}}) \quad \text{and} \\ [I(\theta)] &= \sum_{t=1}^{T} E[\frac{\partial \ell_t}{\partial \theta}\frac{\partial \ell_t}{\partial \theta'}] \end{aligned}$$

Under the assumption of multivariate normality of u_t, the contribution of t^{th} observations to the loglikelihood is

$$\ell_t = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|R_t| - \frac{1}{2}\ln|D_t^2| - \frac{1}{2}u_t' H_t^{-1} u_t$$

then derivative of this function with respect to the variance parameter vector of series i: $w_i = [\alpha_{0,i}\ \alpha_{1,i}\ \beta_{1,i}]'$ is

$$\begin{aligned} \frac{\partial \ell_t}{\partial w_i} &= -(\frac{\partial h_{ii,t}}{\partial w_i}\underbrace{\frac{\partial (vecD_t)'}{\partial h_{ii,t}}}_{(1)}\underbrace{\frac{\partial(\ln|D_t|)}{\partial(vecD_t)}}_{(2)}) \\ &\quad -\frac{1}{2}(\frac{\partial h_{ii,t}}{\partial w_i}\underbrace{\frac{\partial (vecD_t^{-1})'}{\partial h_{ii,t}}}_{(3)}\underbrace{\frac{\partial (vecH_t^{-1})'}{\partial (vecD_t^{-1})}}_{(4)}\underbrace{\frac{\partial u_t' H_t^{-1} u_t}{\partial (vecH_t^{-1})}}_{(5)}) \end{aligned} \tag{2.39}$$

the term (1) is equal to

$$(1) \Longrightarrow \frac{\partial (vecD_t)'}{\partial h_{ii,t}} = \frac{1}{2\sqrt{h_{ii,t}}}[M_i^N]'$$

where M_i^N is a $N^2 \times 1$ column vector whose i^2 element is 1 and other elements are

0. The term (2) is equal to

$$(2) \Longrightarrow \frac{\partial(\ln|D_t|)}{\partial(vecD_t)} = vec(\frac{\partial(\ln|D_t|)}{\partial D_t}) = vec(D_t^{-1})$$

The term (3) is equal to

$$(3) \Longrightarrow \frac{\partial(vecD_t^{-1})'}{\partial h_{ii,t}} = -\frac{1}{2h_{ii,t}\sqrt{h_{ii,t}}}[M_i^N]'$$

The term (4) is equal to

$$\begin{aligned}
(4) \quad \Longrightarrow \quad & \frac{\partial(vecH_t^{-1})'}{\partial(vecD_t^{-1})} = \frac{\partial(vecD_t^{-1}R_t^{-1}D_t^{-1})'}{\partial(vecD_t^{-1})} \\
= \quad & (D_t^{-1}R_t^{-1} \otimes I_N + I_N \otimes D_t^{-1}R_t^{-1})' \\
= \quad & (D_t^{-1}R_t^{-1} \otimes I_N)' + (I_N \otimes D_t^{-1}R_t^{-1})' \\
= \quad & [(D_t^{-1}R_t^{-1})' \otimes (I_N)'] + [(I_N)' \otimes (D_t^{-1}R_t^{-1})'] \\
= \quad & [(R_t^{-1}D_t^{-1} \otimes I_N) + (I_N \otimes R_t^{-1}D_t^{-1})]
\end{aligned}$$

The term (5) is equal to

$$\begin{aligned}
(5) \quad \Longrightarrow \quad & \frac{\partial u_t' H_t^{-1} u_t}{\partial(vecH_t^{-1})} = vec(\frac{\partial u_t' H_t^{-1} u_t}{\partial H_t^{-1}}) = vec(u_t u_t') \\
= \quad & (u_t \otimes u_t)
\end{aligned}$$

the product of terms (1)(2) equals to

$$(1)(2) = \frac{1}{2\sqrt{h_{ii,t}}}[M_i^N]'vec(D_t^{-1}) = \frac{1}{2h_{ii,t}}$$

the product of terms (4)(5) equals to

$$\begin{aligned}
(4)(5) \quad = \quad & [(R_t^{-1}D_t^{-1} \otimes I_N) + (I_N \otimes R_t^{-1}D_t^{-1})](u_t \otimes u_t) \\
= \quad & (R_t^{-1}D_t^{-1} \otimes I_N)(u_t \otimes u_t) + (I_N \otimes R_t^{-1}D_t^{-1})(u_t \otimes u_t) \\
= \quad & (R_t^{-1}\varepsilon_t \otimes u_t) + (u_t \otimes R_t^{-1}\varepsilon_t) \\
= \quad & (v_t \otimes u_t) + (u_t \otimes v_t)
\end{aligned}$$

multiply this product with the term (3)

$$\begin{aligned}
(3)(4)(5) \quad = \quad & -\frac{1}{2h_{ii,t}\sqrt{h_{ii,t}}}[M_i^N]'[(v_t \otimes u_t) + (u_t \otimes v_t)] \\
= \quad & -\frac{\varepsilon_{i,t}v_{i,t}}{h_{ii,t}}
\end{aligned}$$

Finally, substitute these two products in to Equation 2.39

$$\begin{aligned}\frac{\partial \ell_t}{\partial w_i} &= -\frac{\partial h_{ii,t}}{\partial w_i}\frac{1}{2h_{ii,t}} + \frac{\partial h_{ii,t}}{\partial w_i}\frac{\varepsilon_{i,t}v_{i,t}}{2h_{ii,t}} \\ &= -\frac{1}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial w_i}(1-\varepsilon_{i,t}v_{i,t})\end{aligned}$$

where $\frac{\partial h_{ii,t}}{\partial w_i} = (1, u_{i,t}^2, h_{ii,t})' + \beta_i \frac{\partial h_{ii,t-1}}{\partial w_i}$. The term $\varepsilon_{i,t}v_{i,t}$ is expressed as $\varepsilon_{i,t}1_i' R_t^{-1}\varepsilon_t$ by Silvennoinen and Teräsvirta (2005). The derivative of loglikelihood function with respect to correlation parameter vector of $\rho = [(veclP_1^*)', (veclP_2^*)']'$ is

$$\begin{aligned}\frac{\partial \ell_t}{\partial \rho} &= -\frac{1}{2}\Big(\frac{\partial (vecR_t)'}{\partial \rho}\underbrace{\frac{\partial(\ln|R_t|)}{\partial (vecR_t)}}_{(1)}\Big) \\ &\quad -\frac{1}{2}\frac{\partial (vecR_t)'}{\partial \rho}\underbrace{\frac{\partial (vecR_t^{-1})'}{\partial (vecR_t)}}_{(2)}\underbrace{\frac{\partial \varepsilon_t' R_t^{-1}\varepsilon_t}{\partial vecR_t^{-1}}}_{(3)}\end{aligned} \tag{2.40}$$

the term (1) is equal to

$$(1) \Longrightarrow \frac{\partial(\ln|R_t|)}{\partial(vecR_t)} = vec\Big(\frac{\partial(\ln|R_t|)}{\partial R_t}\Big) = vecR_t^{-1}$$

the term (2) is equal to

$$(2) \Longrightarrow \frac{\partial (vecR_t^{-1})'}{\partial (vecR_t)} = -(R_t^{-1}\otimes R_t^{-1})'$$

the term (3) is equal to

$$\begin{aligned}(3) \quad \Longrightarrow \quad & \frac{\partial \varepsilon_t' R_t^{-1}\varepsilon_t}{\partial vecR_t^{-1}} = vec\Big(\frac{\partial \varepsilon_t' R_t^{-1}\varepsilon_t}{\partial R_t^{-1}}\Big) = vec(\varepsilon_t\varepsilon_t') \\ = \quad & (\varepsilon_t \otimes \varepsilon_t)\end{aligned}$$

so the derivative is

$$\frac{\partial \ell_t}{\partial \rho} = -\frac{1}{2}\frac{\partial (vecR_t)'}{\partial \rho}(vecR_t^{-1} - (R_t^{-1}\otimes R_t^{-1})(\varepsilon_t \otimes \varepsilon_t))$$

where $\frac{\partial (vecR_t)'}{\partial \rho} = [1, -s_t]' \otimes U_t$. ($U_t$ is an $N^2 \times N(N-1)/2$ matrix whose columns are $[vec(1_i 1_j' + 1_j 1_i')]_{i=1,\ldots N-1,\ j=i+1,\ldots N}$)

From the definition of information matrix $[I(\theta)] = \sum_{t=1}^{T} E[\frac{\partial \ell_t}{\partial \theta}\frac{\partial \ell_t}{\partial \theta'}]$ where $\theta = [w_1, ..., w_N, \rho]$.

For $N = 2$, it looks like

$$[I(\theta)] = \sum_{t=1}^{T} E \begin{bmatrix} \frac{\partial \ell_t}{\partial w_1}\frac{\partial \ell_t}{\partial w_1'} & \frac{\partial \ell_t}{\partial w_1}\frac{\partial \ell_t}{\partial w_2'} & \frac{\partial \ell_t}{\partial w_1}\frac{\partial \ell_t}{\partial \rho'} \\ \frac{\partial \ell_t}{\partial w_2}\frac{\partial \ell_t}{\partial w_1'} & \frac{\partial \ell_t}{\partial w_2}\frac{\partial \ell_t}{\partial w_2'} & \frac{\partial \ell_t}{\partial w_2}\frac{\partial \ell_t}{\partial \rho'} \\ \frac{\partial \ell_t}{\partial \rho}\frac{\partial \ell_t}{\partial w_1'} & \frac{\partial \ell_t}{\partial \rho}\frac{\partial \ell_t}{\partial w_2'} & \frac{\partial \ell_t}{\partial \rho}\frac{\partial \ell_t}{\partial \rho'} \end{bmatrix}$$

thus, the calculation of following expectations are needed.

$$\begin{aligned} (1) &: E[\frac{\partial \ell_t}{\partial w_i}\frac{\partial \ell_t}{\partial w_i'}] \\ (2) &: E[\frac{\partial \ell_t}{\partial w_i}\frac{\partial \ell_t}{\partial w_j'}] \\ (3) &: E[\frac{\partial \ell_t}{\partial w_i}\frac{\partial \ell_t}{\partial \rho'}] \\ (4) &: E[\frac{\partial \ell_t}{\partial \rho}\frac{\partial \ell_t}{\partial \rho'}] \end{aligned}$$

Silvennoinen and Teräsvirta (2005) provide the expectations when evaluated under the null hypothesis of $vecl P_2^* = 0$.

$$(1) = \frac{1}{4h_{ii,t}^2}\frac{\partial h_{ii,t}}{\partial w_i}\frac{\partial h_{ii,t}}{\partial w_i'}(1 - 1_i' P_1^{*-1} 1_i)$$

$$(2) = \frac{1}{4h_{ii,t}h_{jj,t}}\frac{\partial h_{ii,t}}{\partial w_i}\frac{\partial h_{jj,t}}{\partial w_j'}(\rho_{1,ij}^* 1_i' P_1^{*-1} 1_j)$$

$$(3) = \frac{1}{4h_{ii,t}}\frac{\partial h_{ii,t}}{\partial w_i}(1_i' P_1^{*-1} \otimes 1_i' + 1_i' \otimes 1_i' P_1^{*-1})\frac{\partial (vec R_t)'}{\partial \rho'}$$

$$(4) = \frac{1}{4}\frac{\partial (vec R_t)'}{\partial \rho}(P_1^{*-1} \otimes P_1^{*-1} + (P_1^{*-1} \otimes I_N)K(P_1^{*-1} \otimes I_N))\frac{\partial (vec R_t)'}{\partial \rho'}$$

Finally the summation of these expectations can be summarized as

$$\begin{aligned} M_1 &= T^{-1}\sum_{t=1}^{T} \varkappa_t \varkappa_t' \odot ((I + P_1^* \odot P_1^{*-1}) \otimes 1_3 \\ M_2 &= T^{-1}\sum_{t=1}^{T} \begin{bmatrix} \varkappa_{1,t} & & 0 \\ & \ddots & \\ 0 & & \varkappa_{N,t} \end{bmatrix} \begin{bmatrix} 1_1' P_1^{*-1} \otimes 1_1' + 1_1' \otimes 1_1' P_1^{*-1} \\ \vdots \\ 1_N' P_1^{*-1} \otimes 1_N' + 1_N' \otimes 1_N' P_1^{*-1} \end{bmatrix} \varkappa_{\rho,t}' \\ M_3 &= T^{-1}\sum_{t=1}^{T} \varkappa_{\rho,t}(P_1^{*-1} \otimes P_1^{*-1} + (P_1^{*-1} \otimes I)K(P_1^{*-1} \otimes I))\varkappa_{\rho,t}' \end{aligned}$$

where $\varkappa_t = (\varkappa_{1,t}, \ldots, \varkappa_{N,t})$ and $\varkappa_{i,t} = -\frac{1}{2h_{ii,t}}\frac{\partial h_{ii,t}}{\partial w_i}$and $\varkappa_{\rho,t} = -\frac{1}{2}[1, -s_t]' \otimes U_t$.Then

the information matrix can be represented by

$$I(\theta) = \begin{bmatrix} M_1 & M_2 \\ M_2' & M_3 \end{bmatrix}$$

take the inverse of this information matrix, then the LM statistic can be calculated.

$$LM_1 = (\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}'})[I(\hat{\theta})]^{-1}(\sum_{t=1}^{T} \frac{\partial \ell_t}{\partial \hat{\theta}})$$

2.3.3.3 Testing for Additional Transition Function

Silvennoinen and Teräsvirta (2009) extend the STCC model to double smooth transition variable (DSTCC) model. The model consists of following mean, variance and correlation equations;

$$\text{Mean Eq: } y_t = \mu_t + u_t$$

$$u_t|\Psi_t \sim (0, H_t)$$

where μ_t is conditional mean vector of series. It can be a function of exogenous and lagged endogenous variables with different parameters for each series

$$\text{Variance Eq: } H_t = D_t R_t D_t$$

$$h_{ii,t} = \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_{i1} h_{ii,t-1}$$

Conditional correlation is defined as a linear combination of four constant extreme correlations as follows.

$$\begin{aligned} \text{Correlation Eq:} \qquad R_t = (1 - G_{2,t})[(1 - G_{1,t})P_{11} + G_{1,t}P_{21}] \\ + G_{2,t}[(1 - G_{1,t})P_{12} + G_{1,t}P_{22}] \end{aligned}$$

$$G_{m,t} = (1 + e^{-\gamma_m(s_{m,t} - c_m)})^{-1} \qquad \gamma > 0 \text{ and } m = 1, 2$$

where the transition functions $G_{1t}(s_{1t}; \gamma_1, c_1)$ and $G_{2t}(s_{2t}; \gamma_2, c_2)$ are logistic functions with different transition variables, different locations and different speed of adjustments. P_{11}, P_{12}, P_{21} and P_{22} are regime specific constant correlations matrices to be estimated.

According to LM_1 test of Silvennoinen and Teräsvirta (2005), the STCC-GARCH model is assumed to be estimated with appropriate transition variable which reject the constant conditional correlation assumption. Then STCC-GARCH model can be tested whether there is a second transition variable, under the restriction that model is STCC-GARCH. Thus the null hypothesis of there is no second transition variable is tested against DSTCC-GARCH model which have two transition functions.

Silvennoinen and Teräsvirta (2009) suggest a test procedure to test STCC-GARCH model for additional transition variable against DSTCC-GARCH model.

If $\gamma_2 = 0$ then the second transition function become a constant of $1/2$ and model reduces to STCC-GARCH model with single transition. However as in the STCC test case, when $\gamma_2 = 0$, an identification problem appears in DSTCC-GARCH model. To this end, first order Taylor approximation is used to calculate approximation for second transition function G_{2t} around $\gamma_2 = 0$. As an analogue to STCC test, the approximation for G_{2t} equals to

$$G_{2,t} \simeq 1/2 + 1/4(s_{2,t} - c_2)\gamma_2$$

and substitute this in to conditional correlation equation,

$$\begin{aligned}
R_t &\simeq (1 - G_{2,t})[(1 - G_{1,t})P_{11} + G_{1,t}P_{21}] + G_{2,t}[(1 - G_{1,t})P_{12} + G_{1,t}P_{22}] \\
&\simeq (1 - G_{1,t})(1/2 + 1/4(s_{2,t} - c_2)\gamma_2)P_{11} + (1 - G_{1,t})(1/2 + 1/4(s_{2,t} - c_2)\gamma_2)P_{12} \\
&\quad + G_{1,t}(1/2 + 1/4(s_{2,t} - c_2)\gamma_2)P_{21} + \quad G_{1,t}(1/2 + 1/4(s_{2,t} - c_2)\gamma_2)P_{22}
\end{aligned}$$

$$\begin{aligned}
&\simeq (1 - G_{1,t})(1/2 - 1/4c_2\gamma_2)P_{11} + (1 - G_{1,t})(1/2 + 1/4c_2\gamma_2)P_{12} \\
&\quad +(1 - G_{1,t})(-1/4s_{2,t}\gamma_2)P_{11} + (1 - G_{1,t})(1/4s_{2,t}\gamma_2)P_{12} \\
&\quad +G_{1,t}(1/2 - 1/4c_2\gamma_2)P_{21} + G_{1,t}(1/2 + 1/4c_2\gamma_2)P_{22} \\
&\quad +G_{1,t}(-1/4s_{2,t}\gamma_2)P_{21} + G_{1,t}(1/4s_{2,t}\gamma_2)P_{22}
\end{aligned}$$

$$\begin{aligned}
&\simeq (1 - G_{1,t}) \underbrace{[1/2(P_{11} + P_{12}) + 1/4(P_{12} - P_{11})c_2\gamma_2]}_{P_1^*} \\
&\quad +G_{1,t} \underbrace{[1/2(P_{21} + P_{22}) + 1/4(P_{22} - P_{21})c_2\gamma_2]}_{P_2^*} \\
&\quad +s_{2,t} \underbrace{[-1/4(1 - G_{1,t})\gamma_2(P_{11} - P_{12}) - 1/4G_{1,t}\gamma_2(P_{21} - P_{22})]}_{P_3^*}
\end{aligned}$$

$$R_t \simeq (1 - G_{1,t})P_1^* + G_{1,t}P_2^* + P_3^* s_{2,t}$$

and auxiliary null hypothesis is $vecl P_3^* = 0$. Therefore with this form of conditional correlation it is seen that after controlling for first transition function with optimal transition variable, the additional transition function test searches for an additional variable which have the potential to affect the conditional correlation. If there exists such a variable then it is assumed that this variable affects conditional correlation through smooth transition dynamics which is described by logistic transition function and DSTCC-GARCH model is estimated.

The test procedure is very similar to STCC test. Since the restricted model is STCC-GARCH model, the derivatives of loglikelihood with respect to first transition function parameters has to be calculated together with variance and correlation parameters. Thus the information matrix has to be augmented to cover parameters of the first transition function, $\varphi_1 = (\gamma_1$ and $c_1)$.

The derivative of loglikelihood function with respect to φ_1,

$$\begin{aligned}\frac{\partial \ell_t}{\partial \varphi_1} &= -\frac{1}{2}(\underbrace{\frac{\partial G_{1,t}}{\partial \varphi_1}\frac{\partial (vecR_t)'}{\partial G_{1,t}}}_{(1)}\underbrace{\frac{\partial (\ln|R_t|)}{\partial (vecR_t)}}_{(2)}) \\ &\quad -\frac{1}{2}(\underbrace{\frac{\partial G_{1,t}}{\partial \varphi_1}\frac{\partial (vecR_t)'}{\partial G_{1,t}}}_{(1)}\underbrace{\frac{\partial (vecR_t^{-1})'}{\partial (vecR_t)}}_{(3)}\underbrace{\frac{\partial \varepsilon_t' R_t^{-1}\varepsilon_t}{\partial vecR_t^{-1}}}_{(4)}\end{aligned}$$

the term (1) is equal to

$$\begin{aligned}(1) \implies \frac{\partial G_{1,t}}{\partial \varphi_1}\frac{\partial (vecR_t)'}{\partial G_{1,t}} &= \frac{\partial G_{1,t}}{\partial \varphi_1}(vecP_2^{*\prime} - vecP_1^{*\prime}) \\ &= G_{1,t}(1-G_{1,t})\begin{bmatrix}\gamma_1 \\ c_1 - s_{1,t}\end{bmatrix} vec(P_1^* - P_2^*)'\end{aligned}$$

the term (2) is equal to

$$(2) \implies \frac{\partial (\ln|R_t|)}{\partial (vecR_t)} = vec(\frac{\partial (\ln|R_t|)}{\partial R_t}) = vecR_t^{-1}$$

the term (3) is equal to

$$(3) \implies \frac{\partial (vecR_t^{-1})'}{\partial (vecR_t)} = -(R_t^{-1}\otimes R_t^{-1})'$$

the term (4) is equal to

$$\begin{aligned}(4) \implies \frac{\partial \varepsilon_t' R_t^{-1}\varepsilon_t}{\partial vecR_t^{-1}} &= vec(\frac{\partial \varepsilon_t' R_t^{-1}\varepsilon_t}{\partial R_t^{-1}}) = vec(\varepsilon_t\varepsilon_t') \\ &= (\varepsilon_t \otimes \varepsilon_t)\end{aligned}$$

thus

$$\frac{\partial \ell_t}{\partial \varphi_1} = -\frac{1}{2}G_{1,t}(1-G_{1,t})\begin{bmatrix}\gamma_1 \\ c_1 - s_{1,t}\end{bmatrix} vec(P_1^* - P_2^*)'[vecR_t^{-1} - (R_t^{-1}\otimes R_t^{-1})(\varepsilon_t\otimes\varepsilon_t)]$$

In addition to four expectations in testing against STCC-GARCH, the following expectations are needed in testing for additional transition variable;

$$
\begin{aligned}
(5) \quad &: \quad E[\frac{\partial \ell_t}{\partial w_i}\frac{\partial \ell_t}{\partial \varphi_1'}] \\
(6) \quad &: \quad E[\frac{\partial \ell_t}{\partial \rho}\frac{\partial \ell_t}{\partial \varphi_1'}] \\
(7) \quad &: \quad E[\frac{\partial \ell_t}{\partial \varphi_1}\frac{\partial \ell_t}{\partial \varphi_1'}]
\end{aligned}
$$

analogous to calculation of previous four expectations,

$$
\begin{aligned}
(5) &= \frac{1}{4h_{ii,t}}\frac{\partial h_{ii,t}}{\partial w_i}(1_i' P_1^{*-1} \otimes 1_i' + 1_i' \otimes 1_i' P_1^{*-1})\frac{\partial (vecR_t)'}{\partial \varphi_1'} \\
(6) &= \frac{1}{4}\frac{\partial (vecR_t)'}{\partial \rho}(P_1^{*-1} \otimes P_1^{*-1} + (P_1^{*-1} \otimes I_N)K(P_1^{*-1} \otimes I_N))\frac{\partial (vecR_t)'}{\partial \varphi_1'} \\
(7) &= \frac{1}{4}\frac{\partial (vecR_t)'}{\partial \varphi_1}(P_1^{*-1} \otimes P_1^{*-1} + (P_1^{*-1} \otimes I_N)K(P_1^{*-1} \otimes I_N))\frac{\partial (vecR_t)'}{\partial \varphi_1'}
\end{aligned}
$$

the summation of these expectations are

$$
\begin{aligned}
M_4 &= T^{-1}\sum_{t=1}^{T}\begin{bmatrix} \varkappa_{1,t} & & 0 \\ & \ddots & \\ 0 & & \varkappa_{N,t} \end{bmatrix}\begin{bmatrix} 1_1' P_1^{*-1} \otimes 1_1' + 1_1' \otimes 1_1' P_1^{*-1} \\ \vdots \\ 1_N' P_1^{*-1} \otimes 1_N' + 1_N' \otimes 1_N' P_1^{*-1} \end{bmatrix}\varkappa_{\varphi_1,t}' \\
M_5 &= T^{-1}\sum_{t=1}^{T}\varkappa_{\rho,t}(P_1^{*-1} \otimes P_1^{*-1} + (P_1^{*-1} \otimes I)K(P_1^{*-1} \otimes I))\varkappa_{\varphi_1,t}' \\
M_6 &= T^{-1}\sum_{t=1}^{T}\varkappa_{\varphi_1,t}(P_1^{*-1} \otimes P_1^{*-1} + (P_1^{*-1} \otimes I)K(P_1^{*-1} \otimes I))\varkappa_{\varphi_1,t}'
\end{aligned}
$$

thus the information matrix can be represented by

$$
I(\theta) = \begin{bmatrix} M_1 & M_2 & M_4 \\ M_2' & M_3 & M_5 \\ M_4' & M_5' & M_6 \end{bmatrix}
$$

take the inverse of this information matrix, then the LM statistic can be calculated.

$$
LM_2 = (\sum_{t=1}^{T}\frac{\partial \ell_t}{\partial \hat{\theta}'})[I(\hat{\theta})]^{-1}(\sum_{t=1}^{T}\frac{\partial \ell_t}{\partial \hat{\theta}})
$$

2.4 Modeling Cycle

The succeeding three chapters contain applications of the conditional correlation modeling to financial markets. Due to time varying structure of correlations among financial markets, conditional correlations are modeled in the context of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models with

direct formulation of time varying conditional correlation. More specifically, smooth transition conditional correlation (STCC-GARCH) and the double smooth transition conditional correlation (DSTCC-GARCH) models of Silvennoinen and Teräsvirta (2005 and 2009) are employed because of their three essential advantages over other direct correlation parametrizations discussed in Section 2.3.

It is preferred to model conditional correlations in bivariate context, rather than analyzing all markets under one specification. Modeling correlation matrix of a multivariate model with more than two series in STCC-GARCH and DSTCC-GARCH framework implicitly impose the condition that the correlation between all pairs must be governed by not only the same transition variable with same lag, but also same threshold value and same slope parameter. As far as the former concerned, this requires the assumption that the correlations between, for example, US and China, and US and UK are governed by same transition variable which may not be realistic. Although it is possible to generalize these models with common transition variable but different slope and threshold parameters, this is quite impractical due to rapidly increasing number of parameters to be estimated and also the positive definiteness of correlation matrix may be difficult to retain as pointed out in Silvennoinen and Teräsvirta (2005 and 2009). Even if one manages to estimate a multivariate model with several transitions functions, the interpretation of parameters may be very difficult and inferences on bivariate dynamics may not be clarified. The empirical results of Chapters 3, 4 and 5 show that generally, different transition variables for different country pairs govern the change from one correlation regime to other and in a few cases, threshold values of common transition variables do not seem to be matching strengthening our view and making a multivariate modeling impractical at least for the variables analyzed here.

This section summarizes the modeling cycle to simplify the discussion in applications. The modeling procedure basically follows the methodology suggested in Silvennoinen and Teräsvirta (2005, 2009) and consists of four steps. First of all, test CCC assumption against STCC-GARCH model with various candidate variables to determine the significant transition variables. Then estimate STCC-GARCH models with these transition variables. In the third step, test the estimated STCC-GARCH models for additional transition and if the null hypothesis of STCC-GARCH model is rejected, estimate the DSTCC-GARCH model with two transition functions.

The estimated models are first assessed for their ability to capture the conditional correlation dynamics via transition between regime specific constant correlations. At this point, the location of the estimated threshold value and the estimated correlation levels corresponding to each regime are very important. If the number of observation above or below the estimated threshold value is very small and/or the difference between correlation regimes is insignificant then it is not possible to

conclude that the transition variable employed in the STCC-GARCH or DSTCC-GARCH models is needed to capture an inherent smooth transition structure of time varying conditional correlation. Thus these unsatisfactory models are eliminated. Next, among the satisfactory models, the best model is selected according to maximum likelihood value, AIC and SIC statistics.

2.4.1 Test against STCC-GARCH Model

Since the transition variable in STCC-GARCH model serves as an explanatory variable in correlation equation and time varying structure of conditional correlation is represented by transition variable, the empirical performance of the model depends on the ability of the transition variable to represent the factors determining the conditional correlation. Hence, the choice of transition variable is very important. The aim of the each study postulates its own candidate and theoretically, any variable can be chosen as a candidate transition variable. However the transition variable employed in the STCC-GARCH estimation should reject the CCC assumption. If the true conditional correlation is constant then parameters in the transition function cannot be identified and this identification problem may lead to inconsistent parameter estimates. Therefore, before estimating the STCC-GARCH model with particular transition variable it is necessary to test the null hypothesis that conditional correlation is constant with respect to this variable. The failure to reject the null does not mean that the conditional correlation is constant. Instead, it implies that the correlation does not vary according to this particular variable which is employed in the test procedure. Hence, various transition variables should be tested and the variable which is most significantly reject the constant conditional correlation hypothesis should be chosen as a transition variable among various transition variables. The relevant candidate variables in examining the dynamic nature of the correlation among the stock markets used in the applied literature can be summarized as;

- Calendar time

  Time is a suitable transition variable to investigate the structure of time trend in conditional correlations among financial markets in a world where these markets have become more and more dependent due to developments in financial markets. As an analogue to time series analysis, if the conditional correlation has a time trend then using variables which may also contain a time trend as a transition variable without a trend term may be misleading. Silvennoinen and Teräsvirta (2009), Aslanidis et. al. (2010) and Savva and Aslanidis (2010) use time as a transition variable.

- VIX index[13]
- Conditional volatility of indices
- Lagged squared errors
- Absolute value of lagged errors

  These four variables are measures of uncertainty and volatility. The first variable, VIX index, is a measure of global risk and indicate the overall market uncertainty or distress. Other three variables are employed as measure of country or index specific volatility. Therefore these variables are appropriate to test the hypothesis that co-movements among financial markets are stronger during turbulence periods than they are during more tranquil periods. Silvennoinen and Teräsvirta (2009) and Aslanidis et. al. (2010) use the VIX index and volatility of stock market indices as a transition variable respectively.

- Lagged errors

  The measures of volatility are always positive so, using these variables can capture the responds of the conditional correlation to the size of the volatility and cannot take the direction of trend or sign in to consideration. To test the hypothesis that the direction of market return also matter as well as the size, the lagged error can be an useful transition variable. Thus, the possible asymmetric behaviors of conditional correlations can be captured. Silvennoinen and Teräsvirta (2005) employs a function of lagged errors as a transition variable.

In Chapters 3, 4 and 5, all of these variables are considered as candidate for transition variable and classified in to four groups. The first group only includes calendar time to check the increasing trend hypothesis, the second one contains VIX index as a measure of global volatility, the third group includes variables to measure index specific volatility which are conditional volatility, lagged squared errors and absolute value of lagged errors, and the last group consists of lagged errors as a measure of good and bad news. As argued by Tse (2002), since correlation is a unit free measure, its dynamics can be better represented by unit free variables. Therefore, in addition to errors, standardized errors are also considered. Before estimating the STCC-GARCH models with these transition variables, to find the significant transition variables among candidate variables, the LM_1 test of Silvennoinen and Teräsvirta

[13]The Chicago Board Options Exchange volatility index, VIX, is constructed using the implied volatilities of a wide range of S&P500 index options.

(2005) is conducted for all variables[14] in each group with their lags. The rejection of CCC assumption implies that the conditional correlation gives significant response to changes in the transition variable. The properties and structures of dynamic conditional correlation can be revealed by estimating STCC-GARCH model which is the next step in modeling cycle and explained in the coming section.

2.4.2 Estimate STCC-GARCH Model

In estimating STCC specification of the conditional correlation, the variable providing the smallest p-value should be selected as the appropriate transition variable. However, it is possible that p-values corresponding to different transition variables may be very close to each other preventing the clear cut selection of one of them. In such cases, the STCC-GARCH model is estimated for all of them and the selection of the appropriate transition variable is postponed to post-estimation.

STCC-GARCH model is estimated with maximum likelihood (ML) under the assumption of conditional normality of standardized errors. Since it is very difficult to estimate all equations (mean, variance, correlation and transition function) jointly at once, the log-likelihood is maximized by sequential iteration. As an attempt to attain the global maximum, grid search is performed over the parameters of the transition function. The parameter values which generate the maximum likelihood value are chosen as initial values and all equations are estimated simultaneously at once with these initial values (For details, see Section 2.3.2.3).

Since the interpretations of parameter estimates are quite problematic due to large number of parameters, the graphs of estimated conditional correlations are employed to interpret the estimation results of the STCC-GARCH and DSTCC-GARCH models. For each STCC-GARCH estimations, two figures are provided. The first figure is the time plot of the conditional correlation and shows the progress of conditional correlation through time. The second figure[15] is the scatter plot of conditional correlation to the transition variable and displays the evolution of conditional correlation to the ordered transition variable.

It should be reminded that the results of STCC-GARCH models should be interpreted cautiously. The rejection of CCC assumption for more than one transition variable may indicate that the estimated STCC-GARCH model using the best transition variable is not adequate to capture the dynamic structure of the conditional correlation and the model needs a second transition variable. Therefore the esti-

[14] To be able to apply the LM test for the standardized errors, they are assumed to be exogenous. Otherwise the derivatives in the test are not manageable to derive the LM statistics.

[15] If the first transition variable is time then there is no need to this figure.

mated STCC-GARCH models should be tested for additional transition function which is described next.

2.4.3 Test for Additional Transition Function

To uncover whether a second transition function is needed, all estimated STCC-GARCH models are tested for additional transition variable with LM_2 test of Silvennoinen and Teräsvirta (2009) by considering same candidate variables of first step as additional transition variables. This step is essential in not only identifying the second transition function, but also proving the optimality of the transition variable choice in the estimating STCC-GARCH model. If the transition variable delivering the best STCC-GARCH model appears as a significant additional transition variable in all other STCC-GARCH models, then it can be concluded that this best transition variable should be one of the transition variables in the best DSTCC-GARCH model. Besides, this test gives an idea about whether each significant transition variable carry specific and unique information on the dynamic structure of conditional correlation which cannot be captured by other variables.

More generally, in the third step the additional transition function test searches for an additional variable which have the potential to affect the conditional correlation after controlling for first transition function with optimal transition variable. If there exists such a variable then it is assumed that this variable affects conditional correlation through smooth transition dynamics which is described by logistic transition function and DSTCC-GARCH model is estimated with determined two transition variables. The estimation of DSTCC-GARCH model is the final step and it is explained below.

2.4.4 Estimate DSTCC-GARCH Model

It is possible that the null hypothesis of STCC-GARCH model with the best transition variable is rejected against the alternative DSTCC-GARCH model for more than one additional transition variables, in this case again DSTCC-GARCH model is estimated for all of them and model selection is deferred to post estimation .Since our aim is to uncover the structure and properties of correlation with respect to interested factors represented by different variable groups, we perform model selection within each variable group, not among all variables.

As in STCC-GARCH estimation, DSTCC-GARCH model can be estimated by maximum likelihood (ML) under the assumption of conditional normality of standardized errors. Once the transition variables are determined the log-likelihood in Section 2.3.2.4 can be constructed and maximized through sequential iteration over each set by holding the parameters of other set at their previously estimated values. In this case the grid search for initial values is performed over the parameters of the two

transition functions which considerably increase the number of estimations. Again, the parameter values generating the maximum ML value are chosen as initial values and whole estimation is started from these initials.

All estimations are performed using RATS 8.0. Our own source code are adapted from the Ox code which is kindly supplied by Annastiina Silvennoinen.

CHAPTER 3

INTEGRATION OF CHINA STOCK MARKET WITH INTERNATIONAL STOCK MARKETS[1]

3.1 Introduction

Financial decision makers prefer to use different kinds of portfolio diversification strategies to reduce risk generated by the uncertainty on future values of their investments. Since portfolio diversification within a single market cannot eliminate systematic risk generated by common dynamics of this market or the economy in which this market operates, portfolio diversification strategies have been extended to international level. International diversification can provide further risk reduction due to the fact that differences exist in levels of economic growth and timing of business cycles among countries.

International portfolio diversification requires low or negative correlations among financial markets to be able to attain lower risk level. However, since the 1987 economic crash, the observations of simultaneous high changes in international financial markets points out that there is an upward trend in the correlation among international financial markets and these markets have become more and more integrated over time due to factors such as developments in information technology, establishment of multinational companies and liberalization of financial systems and capital markets. It is now well documented that the correlation among financial markets in developed countries is very high and the benefits of international portfolio diver-

[1] Materials from this chapter are presented at the 2011 Meetings of the Midwest Econometrics Group October 6-7, The Booth of School of Business, University of Chicago.

sification among developed markets become very limited. This fact suggests that investors should look for an emerging market whose correlation with international financial markets is low and which have potential to grow fast.

A popular alternative among emerging financial markets is China. China offers huge opportunities in all areas of economy to investors due to its large economic scale and impressive economic growth. The economic performance of China during the last two decades is very striking. Despite the global financial turmoil since 2008, Chinese economy has achieved to keep growing at quite high rates while many developing and developed economies have been experiencing low or negative economic growth. China's two stock markets, the Shanghai Securities Exchange (Shgh) and the Shenzhen Stock Exchange (Shzh), are established on December 19, 1990 and July 3, 1991, respectively. The shares initially listed on these stock markets are called A-shares, and they could only be traded by Chinese citizens and denominated in Renminbi. Starting in early 1992, another category of shares, known as B-shares, is introduced in these two stock markets and B-shares could only be traded by foreign investors. They are denominated in Renminbi, but traded in foreign currency. All transactions and dividend payments of B-shares are in US dollars in Shanghai stock market and Hong Kong dollars in Shenzhen stock market. The number of listed companies has grown very rapidly from 53 to 894 since 1992. Now, at the end of 2010, Shanghai Stock Exchange is the world's 5th largest stock market by market capitalization which is about US$2.7 trillion.

China has initiated several structural reforms and liberalization policies since 1999 with the introduction of security law. In 2001 domestic investors start to trade B-shares. Following the introduction of qualified foreign institutional investor program, which relax the restriction on A-shares, qualified foreign investors start to trade A-shares in July, 2003. Since May, 2006 qualified domestic institutional investors are allowed to invest in foreign developed stock markets. These two programs are among the commitments of China to liberalize its financial markets during its admission to the World Trade Organization (WTO) in December, 2001. Besides, China also commits to list its large state-owned enterprises on foreign stock markets and let foreign enterprises be listed on the stock markets in China. However these two policy actions took place at the end of 2006. With these structural reforms, China seems to be dedicated to become one of the largest world economies and to rapidly integrate with the rest of the world economies. As a result of economic integration of China with the rest of the world, significant increases in the correlations between Chinese stock markets and stock markets in the developed financial markets are expected. However, empirical applications in the finance literature cannot detect an evidence of increasing trend in the conditional correlation of stock markets in China with major developed countries so far.

In order to address the issue whether stock markets in China can provide diversification benefits, this chapter investigates the dynamic structure of the interdependence among Chinese stock markets and stock markets in four developed countries, namely the US, UK, France and Japan. The analysis covers both A-share and B-share indices of Chinese stock market. To incorporate the fact that the conditional correlations among international stock markets are time varying, the conditional correlations between stock markets in each one of the eight country pairs (i.e. China-A – US, China-A – UK, China-A – France and China-A – Germany, and same pairs for China-B) are modeled in the context of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) with time varying conditional correlations by using smooth transition conditional correlation (STCC-GARCH) and double smooth transition conditional correlation (DSTCC-GARCH) models developed by Silvennoinen and Teräsvirta (2005 and 2009) and discussed in detail in the previous Chapter. These models are employed for China for the first time in the literature.

First of all, this chapter seeks for an evidence of increasing trend in the conditional correlation among Chinese stock market and stock markets in the US, UK, France and Japan which has not been identified so far in the literature. This can be done by employing calendar time as transition variable in STCC-GARCH model. If the constant conditional correlation assumption is rejected in favor of STCC-GARCH model with time being the transition variable, it is possible to conclude that there is a kind of trend in the conditional correlation whose structure can be revealed by the estimated model parameters. Empirical results are in line with our expectations and they indicate rising trends. Then by considering several measures of global volatility, index specific volatility and the sign of the news from the indices as candidate transition variables in the context of STCC-GARCH and DSTCC-GARCH models, the effects of these factors on the conditional correlations are investigated. The empirical results imply that the correlation structures are highly affected by market volatility with volatile periods leading to lower correlations compared to the more tranquil periods for A-share but the results are mixed for B-share index.

3.2 Literature Survey

In the literature the correlation structure of various countries' and regions' financial markets have been examined by various type of time varying correlation within the multivariate GARCH framework. Although it is evident from the daily observation of financial markets, empirical results do not support increasing trend in co-movements among financial markets up to year 2000s. After 2000, the findings in the literature imply that the correlations among financial markets have tended to increase over time. This result is more apparent among developed countries and for countries in the same region. In the literature, there is very limited number of

studies examining the correlation structure of China with other markets and none of them can identify an increasing trend in the correlation among stock markets in China and developed countries.

Li (2007) uses BEKK specification to examine the linkages between stock markets in China and the US with daily data from January, 2000 to August, 2005 and finds that there is no direct spillover between the US and China stock markets. Lin et al. (2009) study the correlation between the China and world stock markets with DCC-GARCH model. With daily data, they find no evidence of an increasing trend in correlation from December 1992 to December 2006 which leads to the conclusion that China stock markets are excellent opportunities to reduce portfolio risk via international diversification for international investors. However, as argued by Moon and Yu (2010) both studies fail to cover the effects of structural reforms and liberalization policies realized in the financial markets of China, which makes stock markets less restricted and more transparent. Using daily return rates from January, 1999 to June, 2007 to investigate the effects of the structural reform, Moon and Yu (2010) detect a structural break at end of 2005, and report symmetric and asymmetric volatility spillover effects from the US to the China stock markets and symmetric volatility spillover effect from China to the US since this date. But they cannot identify an evidence of increasing trend.

3.3 Data and Empirical Results

3.3.1 Data

Daily closing price of Shanghai Securities Exchange A-shares index (Shgh-A) and B-shares index (Shgh-B), S&P500 index in the US, FTSE index in UK, CAC index in France, and Nikkei index in Japan are collected from Global Financial Data. The daily price data is transformed to continuously compounding weekly returns by log-differencing[2] Thursday closing prices. The sample contains 1002 weekly observations[3] from December 20, 1990 to December 30, 2010 for Shgh-A and 938 weekly observations[4] from February 27, 1992 to December 30, 2010 for Shgh-B. Weekly returns are preferred to alleviate the possible effects of different opening hours. An aggregation over time is expected to weaken these effects. The choice of Thursday

[2] $R_{it} = (\log(P_{it}) - \log(P_{it-1})) \times 100$, where P_{it} is the Thursday closing price of stock market i at time t.

[3] The period from December 20, 1990 to December 30, 2010 consists of 1046 weeks. 60 observations are missing for Shgh-A. 44 of them are deleted from the sample and 16 are replaced by the average value of previous and next week return rates.

[4] The period from February 27, 1992 to December 30, 2010 consists of 983 weeks. 59 observations are missing for Shgh-B. 45 of them are deleted from the sample and 14 are replaced by the average value of previous and next week return rates.

closing price in calculating weekly return, instead of using end-of-week closing price, is an attempt to avoid any possible end-of-week effects. All indices are denominated in local currencies to exclude the possible effects of exchange rate volatility. The extremely positive returns which are outside the four standard deviations confidence interval around the mean are replaced by mean plus four standard deviation and the extreme negative returns are treated in the same way. This truncation is necessary for Shgh-A index in estimation of GARCH parameters. Otherwise, estimated GARCH parameters do not meet the positivity and stability conditions of GARCH process. This truncation also mitigates the effects of outliers on LM tests used in determining appropriate transition variables.

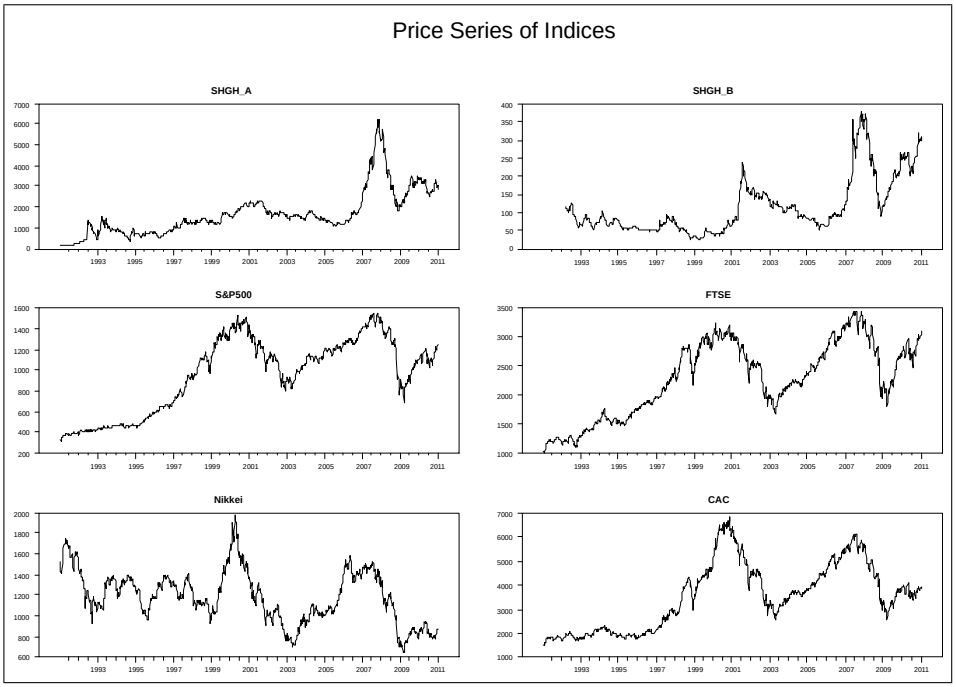


Figure 3.1: Weekly price series of Shgh-A, Shgh-B, S&P500, FTSE, Nikkei and CAC

Figures 3.1 and 3.2 indicate the evolution of price and weekly return series through time. It is clear from the former Figure that it is possible to divide indices in three groups: indices in China, indices in west developed countries of the US, UK and France, and index in Japan. Before 2004, very similar dynamics are shared by the indices within each group. However after 2004 all indices share common trends: since 2004, they all started to increase and reached to their specific peaks in 2008 then decreasing trend dominates the all indices up to mid-2009 after which recovery phase starts.

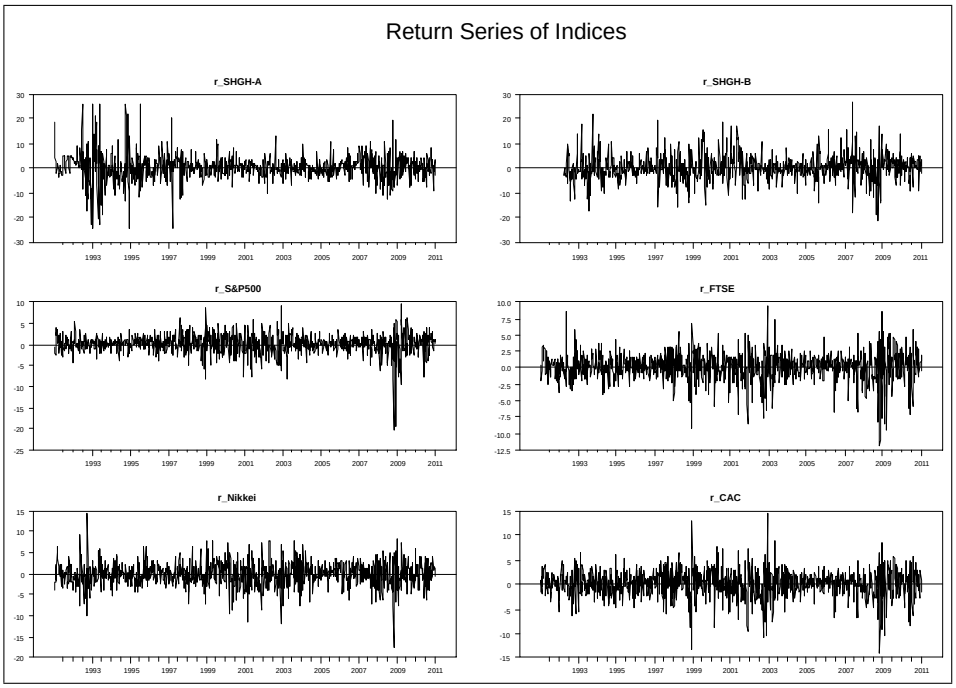


Figure 3.2: Weekly return series of Shgh-A, Shgh-B, S&P500, FTSE, Nikkei and CAC

As return series of indices in Figure 3.2 indicate, the parts experiencing increasing trends of this common period corresponds to low volatile period but the volatility increase to high levels in 2008 and 2009 when the indices are in downward phase. The volatility is also at high levels during the years between 1997 and 2003 which witness the Asian and Russian financial crises and internet companies' crash.

Table 3.1: Descriptive statistics of weekly return rates

	Mean	SD	Skewness	Kurtosis (excess)
Shgh-A	0.3317	6.3519	3.919	51.450
Shgh-B	0.1009	5.3150	0.363	2.773
S&P500	0.1336	2.3709	-1.449	10.740
FTSE	0.109	2.2388	-0.6505	3.459
CAC	0.0907	2.847	-0.417	2.528
Nikkei	-0.056	2.8706	-0.242	2.6409

Table 3.1 summarizes the descriptive statistics of weekly return rates of indices. During the sample period, the better performance of Shgh-A share relative to other indices can easily be seen. Its mean return rate is 3 times higher than average mean return of other indices. An interesting feature revealed by Table 3.1 is that although identical shares are traded in both Shgh-A and Shgh-B, the mean return of Shgh-B is much lower than Shgh-A (it is in fact one third of Shgh-A) and it is also lower

than mean return rates of S&P500. The possible reasons of this difference in Shgh-A and Shgh-B indices may be potential information advantage of domestic investors, the illiquidity of the B-share market and speculation premium for A-share markets[5].

The second stylized fact which is not surprising is that Shgh-A and Shgh-B indices' returns are more volatile. Except Shgh-A and Shgh-B, all indices are left skewed which means that the majority of the return rates are higher than its mean and limited number of, but larger, negative returns reduce the mean. On the other hand, the majority of the returns in Shgh-A and Shgh-B indices are less than their means and larger but limited number of positive returns raises the mean. Although high standard deviation of Shgh-A and Shgh-B share indices imply that these two indices are more risky than other indices, right skewness of Shgh-A and Shgh-B share indices imply that large negative returns are not as likely as large positive returns which means that these two indices are not more risky in terms of losses. The fat tail property of financial time series is also apparent from the excess kurtosis of all indices.

Table 3.2: Sample correlations of weekly return rates

	Shgh-A	Shgh-B	S&P500
Shgh-B	0.5988	1	
S&P500	0.0293	0.0423	1
FTSE	0.0936	0.0968	0.7326
CAC	0.0834	0.0645	0.7363
Nikkei	0.1141	0.0586	0.4348

The unconditional correlations of Shgh-A, Shgh-B and S&P500 indices with each other's, and with FTSE, CAC and Nikkei from weekly return rates are reported in Table 3.2. The correlations of developed countries with both Shgh-A and Shgh-B indices are very low which support the result of Lin et al. (2009) that investing in China Stock market reduces the portfolio risk of international investors. Since B shares are traded by foreigners, the correlation of B-share index is higher than A-shares, as anticipated, but the increase is not too much. Interestingly, although identical shares are traded in both Shgh-A and Shgh-B markets the correlation between these markets is lower than the correlation between developed countries' stock markets indices.

[5]For detailed discusion, see Fernald and Rogers (2002), Karolyi and Li (2003), Mei et al. (2003) and Chan et al. (2007).

3.3.2 Empirical Results

For ease of discussion, mean, variance and correlation equations of STCC and DSTCC specifications which are introduced in the second Chapter are reproduced with brief descriptions.

$$\begin{aligned} \text{Mean Eq.} \qquad y_{i,t} &= \mu_{i0} + \sum_{l=1}^{L_i} \mu_{il} y_{i,t-l} + u_{it} \\ u_t|\Psi_t &\sim (0, H_t) \end{aligned} \tag{3.1}$$

The mean equation for each stock market index is formulated as autoregressive ($AR(L_i)$) process with different lag length which is enough to eliminate the linear dependence in errors of each series.

$$\begin{aligned} \text{Variance Eq.} \qquad H_t &= D_t R_t D_t \\ h_{ii,t} &= \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_{i1} h_{ii,t-1} \end{aligned} \tag{3.2}$$

Since the performance of GARCH(1,1) model is sufficient to represent many dynamics of financial time series, each element of D_t, i.e. each variance is modeled as GARCH(1,1) process separately[6]. To allow for different location and speed of transition and to be able take country specific factors in determining correlations in to account, conditional correlations are modeled in bivariate context.The conditional correlation is defined as a linear combination of two and four constant extreme correlations in STCC-GARCH and DSTCC-GARCH models, respectively. The correlation equation of former is

$$\begin{aligned} \text{Corr Eq.} \qquad R_{ij,t} &= P_{1,ij}(1 - G_t) + P_{2,ij} G_t \\ G_t &= (1 + e^{-\gamma(s_t - c)})^{-1} \quad \gamma > 0 \end{aligned} \tag{3.3}$$

and the more general correlation equation of latter is

$$\begin{aligned} \text{Correlation Eq} \qquad R_{ij,t} &= (1 - G_{2,t})[(1 - G_{1,t}) P_{11,ij} + G_{1,t} P_{21,ij}] \\ &\quad + G_{2,t}[(1 - G_{1,t}) P_{12,ij} + G_{1,t} P_{22,ij}] \end{aligned} \tag{3.4}$$

$$G_{m,t} = (1 + e^{-\gamma_m (s_{m,t} - c_m)})^{-1} \quad \gamma > 0 \text{ and } m = 1, 2$$

where i = Shgh-A and Shgh-B

j = S&P500, FTSE, CAC and Nikkei

---

[6]For Shgh-B, GARCH(3,1) eliminates the dependence in squared standardized errors.

3.3.2.1 STCC-GARCH Model

Although time is the appropriate transition variable for capturing evidence of increasing trend, up to four lags of all variables from other three variable groups, global volatility (VIX), index specific volatility (lagged conditional variance[7], lagged absolute error and lagged absolute standardized error[8], lagged squared error and lagged squared standardized errors) and the effect of good and bad news (lagged errors and lagged standardized error), are also employed not only to uncover the role of these variables in explaining dynamic structure of conditional correlation in the STCC-GARCH and DSTCC-GARCH modeling framework but also to make sure that time is the optimal transition variable. In modeling sequence of both STCC-GARCH and DSTCC-GARCH specifications, variables derived for S&P500, HSI, and Nikkei indices are considered in addition to the variables corresponding to the indices under investigation. This in turn produces 117 candidates for transition variable including their lags for S&P500 and Nikkei, and 145 candidates for FTSE and CAC that need to be included in LM tests for both testing the single and double transition function hypothesis.

The significant transition variables in STCC-GARCH modeling of conditional correlation of Shgh-A and Shgh-B with S&P500, FTSE, CAC, and Nikkei are reported in Tables 3.3 and 3.4 respectively. As seen in Table 3.3, the null hypothesis of CCC against STCC-GARCH model with time transition variable is rejected for S&P500, FTSE and CAC at 1% significance levels and it is rejected for Nikkei at 5% significance level. Besides, LM_1 tests deliver minimum p-value for the time variable except S&P500. For the latter, time is the second most significant variable following a volatility measure of Shgh-A, second lag of absolute error of standardized error. However this case is not valid for Shgh-B index; time variable, except S&P500 case, cannot generate the minimum p-value and the null hypothesis for time variable can be rejected at 1% significance level for only S&P500. It is rejected at 5% significance level for CAC and FTSE, but cannot be rejected for Nikkei (see Table 3.4). The strong rejection of CCC assumption with respect to time variable means that there is a trend in the conditional correlation and the structure of this trend can be revealed by estimating the STCC-GARCH model with time transition variable.

In addition to time variable, as Table 3.3 clearly indicates, the volatility of Shgh-A index which is measured by absolute value of standardized error of this market is a common determinant of dynamic conditional correlation between Shgh-A and other

[7] Conditional variance series are generated by univariate GARCH(1,1) model for each index separately.

[8] Errors are from GARCH(1,1) model and standardized errors are generated by dividing errors to square root of conditional variance.

Table 3.3: Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable for Shgh-A Index

Shgh-A					
S&P500			Nikkei		
Transition Variable	LM-stat.	ρ-value	Transition Variable	LM-stat.	ρ-value
Time	7.340^a	0.007	Time	6.470^b	0.011
A[err.Ch]-L2	6.627^a	0.010	err.HK-L2	3.942^b	0.047
A[serr.Ch]-L2	8.019^a	0.005	serr.HK-L2	4.411^b	0.036
S[serr.Ch]-L2	5.182^b	0.023			
serr.Ch-L1	3.455^c	0.063			
S[err.Ch]-L2	3.306^c	0.069			
err.US-L1	3.356^c	0.067			
FTSE			CAC		
Time	9.873^a	0.002	Time	9.341^a	0.002
A[serr.Ch]-L2	4.261^b	0.039	A[err.Ch]-L2	4.326^b	0.037
			A[serr.Ch]-L2	3.746^c	0.053

Notes: This table represents the LM statistic to test constant conditional correlation null hypothesis with respect to particular transition variable.The LM statistics is evaluated with the estimated parameters from the restricted model of CCC reported in Appendix A.1. (see Silvennoinen and Teräsvirta, 2005). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets, respectively."-Li" is the i^{th} lag of the particular variable."Ch", "US" and "HK" represent Shgh-A, S&P500 and HSI indices. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively.

indices, except Nikkei. However measure of global volatility (VIX index) and the volatility measures of S&P500, FTSE, CAC and Nikkei do not play any significant role. Similarly, types of news from FTSE, CAC and Nikkei are not responsible for dynamic conditional correlation. To summarize, the determinants of conditional correlations between Shgh-A and

- S&P500 are time, four measures of the volatility of Shgh-A (second lag of square and absolute value of error and standardized error of Shgh-A) and the news from both Shgh-A and S&P500 indices represented by first lag of standardized error of Shgh-A and error of S&P500
- FTSE are time and the volatility of Shgh-A (second lag of absolute value of standardized error of Shgh-A)
- CAC are time and two measures of the volatility of Shgh-A (second lag of absolute value of error and standardized error of Shgh-A)
- Nikkei are time and news from HSI index in Hong Kong (second lag of error and standardized error of HSI).

For Shgh-B index, the Table 3.4 reveals that the conditional correlations between Shgh-B and other indices are not affected by any information from Shgh-B index,

they are dominated by S&P500, FTSE, CAC, HSI and Nikkei related information which may reflect the fact that B-shares are restricted to be traded by only foreign investors until 2001 and A-shares can be traded by only domestic investors until mid-2003. Like Shgh-A case, VIX index cannot explain the dynamic structure of conditional correlation between Shgh-B and other indices.

Table 3.4: Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable for Shgh-B Index

Shgh-B					
S&P500			Nikkei		
Transition Variable	LM-stat.	ρ-value	Transition Variable	LM-stat.	ρ-value
Time	9.941^a	0.001	err.US-L2	6.760^a	0.009
err.US-L2	4.396^b	0.036	serr.US-L2	7.174^a	0.007
serr.US-L2	5.536^b	0.018	err.HK-L2	7.192^a	0.044
err.HK-L2	4.831^b	0.027	serr.HK-L2	6.489^b	0.039
serr.HK-L2	4.952^b	0.026	A[serr.US]-L1	4.048^b	0.007
A[err.Jap]-L3	4.828^b	0.028	S[serr.US]-L1	4.234^b	0.011
FTSE			CAC		
Time	4.213^b	0.040	Time	5.429^b	0.019
serr.UK-L2	5.020^b	0.025	A[err.Fr]-L1	3.903^b	0.048
A[err.UK]-L2	10.73^a	0.001	A[err.Fr]-L2	6.004^b	0.014
S[err.UK]-L1	4.663^b	0.031	A[serr.Fr]-L1	4.368^b	0.036
A[serr.UK]-L2	12.93^a	0.000	A[serr.Fr]-L2	7.458^a	0.006
S[serr.UK]-L2	8.909^a	0.002	S[err.Fr]-L1	4.227^b	0.039
err.US-L2	6.910^a	0.008	S[serr.Fr]-L1	5.118^b	0.023
serr.US-L2	7.861^a	0.005	S[serr.Fr]-L2	5.636^b	0.017
A[err.US]-L2	4.550^b	0.033	serr.US-L2	3.924^b	0.047
S[err.US]-L2	5.998^b	0.014	A[err.US]-L2	4.376^b	0.036
A[serr.US]-L2	7.899^a	0.005	S[err.US]-L2	4.703^b	0.030
S[serr.US]-L2	14.67^a	0.000	A[serr.US]-L2	9.113^a	0.002
err.HK-L2	4.991^b	0.025	S[serr.US]-L2	14.75^a	0.000
serr.HK-L2	5.117^b	0.023	S[err.Jap]-L3	4.367^b	0.037
A[serr.HK]-L1	4.980^b	0.025	A[err.Jap]-L3	4.259^b	0.039
A[serr.Jap]-L1	4.360^b	0.036			

Note: See Table3.3

Other than time variable, measures of the news from both S&P500 and HSI, and the volatility of Nikkei are common determinant of the dynamic conditional correlation between Shgh-B and other indices. Except for the correlation with S&P500, volatility of S&P500 index conveys significant information about time varying nature of conditional correlation between Shgh-B and FTSE, CAC and Nikkei. Again except for S&P500, the conditional correlation between Shgh-B and other indices are affected by own volatility of other indices. Thus, the determinant of conditional correlation between Shgh-B and

- S&P500 are time, the news from both S&P500 and HSI, and volatility of Nikkei
- FTSE are time, the news from S&P500, HSI and FTSE, and volatility of Nikkei, S&P500, HSI and FTSE
- CAC are time, the news from S&P500 and volatility of Nikkei, S&P500 and CAC
- Nikkei are the news from both S&P500 and HSI, and volatility of S&P500

The STCC-GARCH models can consistently be estimated with the significant transition variables of Tables 3.3 and 3.4 for eight bivariate cases. In conventional smooth transition modeling[9], STCC-GARCH specification is estimated with the variable providing the smallest p-value. However, since the LM_1 test delivers close p-values for various transition variables (see Tables 3.3 and 3.4), STCC-GARCH model is estimated for all these transition variables and the selection of optimal one is left to post estimation. Table 3.5 presents the estimation results of conditional correlation equation for each pair which correspond to best fit according to ML value[10]. The results show that for all pairs of Shgh-A, time variable provides the best fit but for Shgh-B pairs, the best model is generated by time variable in only S&P500 case.

As discussed in the previous Chapter, more than one significant transition variables indicated by LM_1 tests may suggest that STCC-GARCH model with one of them may be misspecified. Therefore empirical results of STCC-GARCH models should be interpreted cautiously as additional transition variable may provide better description with the estimation of DSTCC-GARCH model. For time variable, before testing STCC-GARCH model for additional transition variable, the estimation results can be interpreted as the average level of conditional correlations over time. Therefore, at this stage among best model of each index pair reported in Table 3.5, the estimation results of STCC-GARCH model with time transition variable are interpreted to reveal the average level of attained conditional correlation through time.

As Figures 3.3 and 3.4 clearly show, there are increasing trends in the conditional correlations between Shgh-A and all developed indices. According to the speed of transition, these trends can be divided in to two groups in which the correlations follow very similar patterns. The first group includes Shgh-A with S&P500 (Figure 3.3). The dynamics of the trend is characterized by two peculiar movements. Up

[9] See Teräsvirta and Anderson (1992), Teräsvirta (1995), and Dijk, Terasvirta and Franses (2002).

[10] The estimation results of all parameters from STCC-GARCH model with stated transition variable are reported in Appendix B.1 with diagnostics.

Table 3.5: The estimation results of STCC-GARCH model with transition variable providing best fit for Shgh-A and Shgh-B indices

			Shgh-A				
	Trans. Var.	ML-value	P_1	P_2	γ	c	H_0:P_1=P_2
S&P500	Time	-4935.22	-0.034	0.214^a	28.3	0.639^a	11.715^a
			(0.040)	(0.059)	(48.2)	(0.074)	[0.000]
FTSE	Time	-4940.48	-0.005	0.261^a	400	0.651^a	18.265^a
			(0.037)	(0.049)	-	(0.006)	[0.000]
CAC	Time	-5169.49	-0.006	0.298^a	400	0.651^a	22.873^a
			(0.04)	(0.044)	-	(0.006)	[0.000]
Nikkei	Time	-5234.21	0.043	0.315^a	400	0.833^a	12.152^a
			(0.035)	(0.061)	-	(0.005)	[0.000]
			Shgh-B				
	Trans. Var.	ML-value	P_1	P_2	γ	c	H_0:P_1=P_2
S&P500	Time	-4773.28	-0.01	1	18.5	0.983^a	567.5^a
			(0.047)	-	(16.4)	(0.033)	[0.000]
FTSE	A[err.UK]-L2	-4773.26	0.004	0.259^a	400	1.343^a	42.743^a
			(0.037)	(0.044)	-	(0.013)	[0.000]
CAC	A[serr.US]-L2	-5001.47	0.034	0.370^a	400	1.32^a	11.278^a
			(0.034)	(0.072)	-	(0.008)	[0.000]
Nikkei	serr.US-L2	-5054.04	0.327^a	0.033	400	-1^a	9.712^a
			(0.09)	(0.036)	-	(0.019)	[0.002]

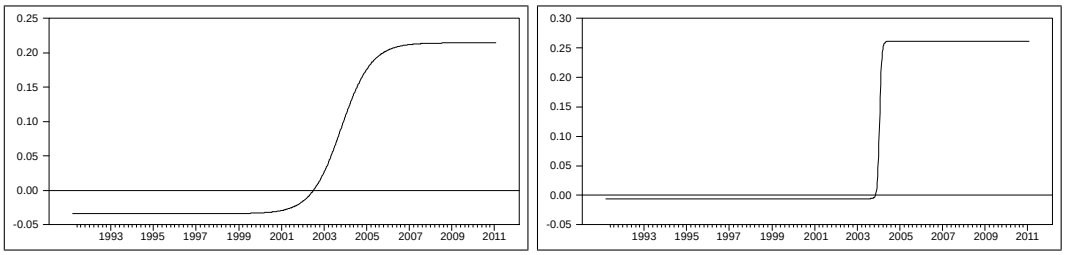
Notes: This table reports the estimation results of parameters in conditional correlation and transition function which is described by equations 3.3 from the STCC-GARCH model with stated transition variable. The mean and variance equations are given by 3.1 and 3.2, respectively. The last column reports the Wald statistics to test the stated null hypothesis. Values in parenthesis and square brackets are standard errors and p-values, respectively. 400 is the upper constraint for speed parameters. (a) denotes significance at 1% level.

to year 2002, there is no significant correlation between Shgh-A and S&P500. However, since then, the conditional correlation started to increase smoothly and finally reached to 0.21 at the end of 2005.

The conditional correlation of Shgh-A with FTSE, CAC and Nikkei constitute the second group. Up to their specific transition date, the conditional correlations with these indices are not significant and very close to zero. Very sharp transitions occurred and the conditional correlations abruptly increased to 0.26 with FTSE and to 0.297 with CAC in January 2004, and 0.315 with Nikkei in August 2007.

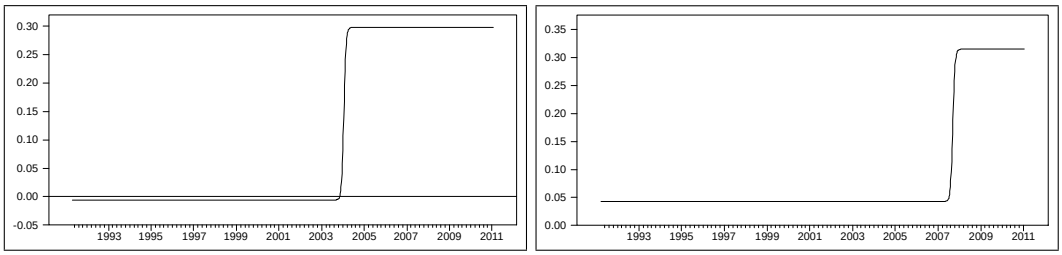
The conditional correlation of Shgh-A index started to increase earlier with S&P500 than other indices (two years earlier than FTSE and CAC, and five and half years earlier than Nikkei) but, at the end of sample, the correlation between Shgh-A and S&P500 is the smallest. The transition to the higher conditional correlation is occurred latest with Nikkei index but the highest correlation level, 0.315, is attained.

The conditional correlation between Shgh-B and S&P500 implied by the STCC-



Shgh-A – S&P500 Shgh-A – FTSE

Figure 3.3: The conditional correlation of Shgh-A with S&P500 and FTSE from STCC-GARCH model with time transition variable



Shgh-A – CAC Shgh-A – Nikkei

Figure 3.4: The conditional correlation of Shgh-A with CAC and Nikkei from STCC-GARCH model with time transition variable

GARCH model with time is depicted in Figure 3.5. The evidence of increasing trend between indices is very apparent. The conditional correlation is characterized by smooth transition and before transition to higher correlation levels, there is no significant conditional correlation. But it starts to increase in 2007 and it is still in transition period rising above 0.5 at the end of 2010. It should be noted that the estimated value of P_2 reaches to its upper boundary of 1. These results may be misleading at this stage and it may be sign of the need for another time variable as second transition variable.

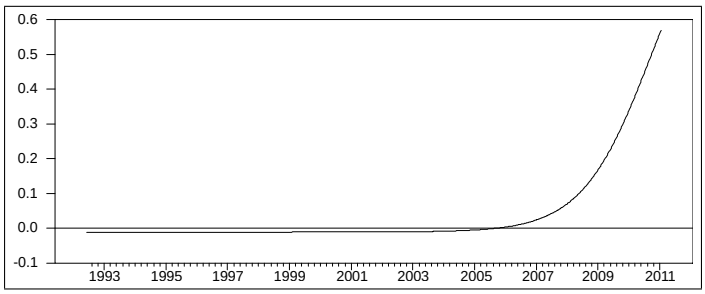


Figure 3.5: The conditional correlation of Shgh-B with S&P500 from STCC-GARCH model with time transition variable

Thus, increasing trend in the conditional correlation of Shgh-A index with S&P500, FTSE, CAC and Nikkei indices and Shgh-B with S&P500 are identified[11]. This finding implies that the opportunities offered by stock markets in China have been decreasing. For each index pair, the estimation results of STCC-GARCH model with time uncover the starting dates of increasing trend and the average levels of correlations reached through time. The starting date of increasing trend between Shgh-A index and other indices ranges from 2002 to 2007. This is not surprising as authorized foreign investors have been allowed to trade in A-shares in 2003. It seems that the regulations following the commitments made by China during its admission to the WTO in December, 2001 have led to integration of stock markets with the rest of the world and hence increasing correlation. These facts can be captured by the models.

In finance literature it is widely accepted view that the beginning of 2000s witnesses the initiation of increasing trend in the correlations among international financial markets. Compared to earlier literature[12], the results show that correlations of stock markets in China with stock markets in developed countries start to increase later than the correlation among developed markets. The findings of recent literature which can be summarized as the correlations between stock markets in China and the major world stock markets[13] are very close to zero, and therefore Chinese stock markets are excellent alternative for risk averse investors who seek for low portfolio risk level via international diversification are partially supported by the results presented above: (i) the correlation is very close to zero, but until 2002, (ii) since then, the conditional correlation has been increasing but the highest correlation level attained through time is much lower than the correlation levels among developed countries, and among developed and developing countries leading the same conclusion that Chinese stock markets can offer relatively valuable opportunities to reduce risk.

Although the sample used in the paper of Lin et al (2009) covers the years when

[11] We search for an evidence of increasing trend in conditional correlation of Shgh-A and Shgh-B with DAX index in Germany, all shares index in Taiwan and Singapore, HSI index in Hong Kong, ASX index in Australia and Kospi index in South Korea. The results indicate that there are upward trends in conditional correlation between Shgh-A and all listed indices. However, increasing trend can only be identified in conditional correlation between Shgh-B, and ASX and Kospi indices. The results are provided in the Appendix G.

[12] Cappiello et al. (2006), Kim et al. (2005), Savva et al. (2009) find that conditional correlations among developed countries have been increasing since the introduction of Euro in 1999. Silvennoinen and Teräsvirta (2009) identify evidence of increasing trend in the conditional correlations among FTSE, DAX, CAC and HIS in the spring of 1999 and Aslanidis et al. (2010) reveal that the correlation between the US and UK shifts to the higher levels around February 2000.

[13] In the literature, the conditional correlation of Chinese stock markets with the stock market in the US, France, Germany, UK, Japan, Australia, Hong Kong, Singapore and Taiwan are investigated.

increasing trend in correlation is started, they cannot identify the increasing trend in the correlation possibly due to their usage of DCC-GARCH model. In DCC-GARCH modeling, the first lags of standardized errors are used as default explanatory variable in the conditional correlation equation. However, as the results show these variables are rarely selected as optimal transition variable and time trend has more dominant explanatory power than standardized errors for the conditional correlation between Shgh-A and all other indices, and between Shgh-B and S&P500. Thus it may be concluded that default explanatory variables in DCC-GARCH models are not appropriate for examining conditional correlation of stock markets in China explaining the poor results of the earlier literature.

The modeling cycle continues with testing the all estimated STCC-GARCH models for evidence of additional transition function. As before, all candidate variables in four variable groups and their lagged values are considered in testing. As far as the transition variables that delivered best STCC-GARCH models and LM_2 test results are concerned, it can be concluded that best variables in STCC-GARCH models should be one of the transition variables in double transition function specification strengthening the inferences derived from the best STCC-GARCH models presented above. However, test results suggest that DSTCC-GARCH model is needed for better characterization. The significant additional transition variables to the estimated best STCC-GARCH models for Shgh-A and Shgh-B are presented in Tables 3.6 and 3.7, respectively.

3.3.2.2 DSTCC-GARCH Model

As expected, null hypothesis is rejected for those transition variables which also appear in single transition modeling with close p-values. This fact requires the estimation of all possible DSTCC-GARCH models with transition variables of Tables 3.6 and 3.7 for each index pair and as before best model and/or transition variables selection is considered in post estimation after eliminating the unsatisfactory models in capturing inherent smooth transition dynamics. As seen, ML values do not allow a clear cut selection among the estimated models possibly due to the fact that most of the candidate transition variables carry similar information regarding the market dynamics. Therefore the best models within each variable group are elaborated to see the similarities and differences as well as to uncover the properties and structure of the conditional correlation with respect to global volatility, index specific volatility and sign of the error. The estimation results of the best models within each variable group[14] are reported in Table 3.8 for Shgh-A and in Table 3.9 for Shgh-B.

[14]For example, for Shgh-A – S&P500 case, there are six significant additional transition variables. Three of them are from the third group representing index specific volatility; second lag of absolute

Table 3.6: LM statistics of testing additional transition variable for Shgh-A pairs

	Shgh-A			
	1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
S&P500	Time	A[err.Ch]-L2	7.291^{a}	0.007
		A[serr.Ch]-L2	9.140^{a}	0.003
		S[serr.Ch]-L2	5.078^{b}	0.024
		VIX-L1	6.192^{b}	0.013
		err.US-L1	5.399^{b}	0.020
		serr.US-L1	3.638^{c}	0.056
		serr.Ch-L1	2.740^{c}	0.098
FTSE	Time	serr.Ch-L4	3.865^{b}	0.049
		A[serr.Ch]-L2	5.025^{b}	0.025
		S[serr.Jap]-L2	5.350^{b}	0.021
CAC	Time	A[err.Ch]-L2	4.490^{b}	0.034
		A[serr.Ch]-L2	4.188^{b}	0.041
		VIX-L3	4.264^{b}	0.039
Nikkei	Time	err.HK-L2	5.003^{b}	0.025
		serr.HK-L2	5.116^{b}	0.024
		A[err.HK]-L3	5.047^{b}	0.025
		S[err.HK]-L3	4.532^{b}	0.033
		VIX-L3	4.433^{b}	0.035

Notes: This table represents the LM statistics of testing estimated STCC-GARCH model with stated first transition variable for additional transition variables. The LM statistics is evaluated with the estimated parameters from the restricted model of STCC-GARCH model (see Silvennoinen and Teräsvirta, 2009). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets, respectively."-Li" is the i^{th} lag of the particular variable."Ch", "US", "UK", "Fr", "Jap" and "HK" represent Shgh-B, S&P500, FTSE, CAC, Nikkei and HSI indices. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively.

Table 3.7: LM statistics of testing additional transition variable for Shgh-B pairs

	Shgh-B			
	1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
S&P500	Time	Time	4.302^{b}	0.038
		S[err.Jap]-L3	6.621^{b}	0.010
		A[err.Jap]-L3	5.599^{b}	0.018
FTSE	A[err.UK]-L2	serr.US-L2	3.852^{b}	0.049
		S[serr.US]-L2	5.005^{b}	0.025
		err.HK-L2	4.063^{b}	0.043
		serr.HK-L2	3.855^{b}	0.049
		S[err.Jap]-L3	4.708^{b}	0.030
		A[err.Jap]-L3	4.992^{b}	0.025
		vol.Jap-L2	5.602^{b}	0.018
		VIX-L3	4.233^{b}	0.039
CAC	A[serr.US]-L2	Time	5.804^{b}	0.016
		A[err.Fr]-L1	5.020^{b}	0.024
		S[err.Fr]-L1	4.320^{b}	0.037
		A[serr.Fr]-L1	6.810^{a}	0.009
		S[serr.Fr]-L1	6.614^{b}	0.010
		A[err.Jap]-L3	4.632^{b}	0.031
		S[err.Jap]-L3	4.225^{b}	0.029
Nikkei	serr.US-L2	err.US-L4	5.266^{b}	0.021
		vol.Jap-L1	3.911^{b}	0.048
		err.Jap-L4	5.284^{b}	0.021

Note: See Table 3.6

The estimated conditional correlations between eight index pairs are plotted and interpreted first for Shgh-A and then for Shgh-B.

value of error of Shgh-A and second lag of square and absolute value of standardized error of Shgh-A as a measure of Shgh-A index volatility. (see Table 3.6). Three DSTCC-GARCH model using time and one of them as transition variable are estimated but only the estimation results of the best model corresponding to second lag of absolute value of standardized error of Shgh-A is reported in Table 3.8. Other three variables are among the measures of good and bad news constituting the fourth group. Two of them, first lag error and standardized error of S&P500, represents the arrival of good or bad news from S&P500 with different scaling. Therefore, among these two measures, the estimation result of DSTCC-GARCH model with transition variables of time and first lag of standardized error of S&P500 which gives better model is also reported in Table 3.8. Hence, instead of reporting estimation results of six models, we report three of them; one for a volatility measure of Shgh-A, one for news from S&P500 and one for news from Shgh-A.

Table 3.8: The estimation results of DSTCC-GARCH models for Shgh-A

Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
					Shgh-A – S&P500						
Time + A[serr.Ch]-L2	-4929.478	0.052	-0.166^a	0.296^a	0.089	71.27^a	400	0.632^a	0.798^a	12.747	5.752
		(0.04)	(0.042)	(0.059)	(0.059)	(13)	-	(0.039)	(0.015)	[0.000]	[0.016]
Time + serr.Ch-L1	-4929.492	0.128^a	-0.149^a	0.202^a	0.312^a	17.33	400	0.727^a	0.005^a	13.907	2.066
		(0.003)	(0.031)	(0.022)	(0.10)	(16)	-	(0.071)	(0.001)	[0.000]	[0.151]
Time + serr.US-L1	-4930.158	-0.19^a	0.063	0.210^b	0.275^a	14.51	400	0.666^a	-0.087^a	8.709	0.310
		(0.061)	(0.062)	(0.095)	(0.065)	(9.5)	-	(0.089)	(0.03)	[0.003]	[0.577]
Time + VIX-L1	-4930.462	0.035	-0.177	1	1	5.254	400	1	20.23^a	3.908	-
		(0.08)	(0.144)	-	-	(4.9)	-	-	(0.164)	[0.048]	-
					Shgh-A – FTSE						
Time + A[serr.Ch]-L2	-4936.814	0.040	-0.119^c	0.337^a	0.126^b	400	400	0.651^a	1.058^a	3.602	8.988
		(0.04)	(0.066)	(0.038)	(0.06)	-	-	(0.005)	(0.024)	[0.057]	[0.003]
Time + serr.Ch-L4	-4935.801	-0.087^c	0.048	0.122^b	0.372^a	400	400	0.652^a	-0.428^a	3.214	9.667
		(0.051)	(0.043)	(0.05)	(0.05)	-	-	(0.005)	(0.013)	[0.073]	[0.002]
					Shgh-A – CAC						
Time + A[serr.Ch]-L2	-5165.291	0.05	-0.116^a	0.372^a	0.162^a	400	400	0.651^a	0.906^a	61.187	14.001
		(0.034)	()0.02	(0.007)	(0.056)	-	-	(0.006)	(0.04)	[0.000]	[0.000]
					Shgh-A – Nikkei						
Time + serr.HK-L2	-5228.582	0.082^b	-0.184^b	0.352^a	-0.018	400	400	0.804^a	0.844^a	7.779	4.307
		(0.04)	(0.087)	(0.066)	(0.165)	-	-	(0.01)	(0.024)	[0.005]	[0.038]
Time + Vix-L3	-5228.866	0.059	0.002	0.621^a	0.198^b	400	400	0.834^a	21.57^a	0.577	12.772
		(0.042)	(0.06)	(0.076)	(0.089)	-	-	(0.003)	(0.022)	[0.447]	[0.000]
Time + A[err.HK]-L3	-5231.045	0.053	-0.067	0.397^a	0.024	400	400	0.834^a	5.933^a	0.644	4.574
		(0.036)	(0.14)	(0.064)	(0.162)	-	-	(0.005)	(0.131)	[0.422]	[0.032]

Notes: See Table 3.9.

3.3.2.2.1 Shgh-A – S&P500: Among four DSTCC-GARCH models, the best fit for conditional correlation between Shgh-A and S&P500 indices is obtained with transition variables time and second lag of absolute value of standardized error of Shgh-A. The conditional correlation implied by the estimated DSTCC-GARCH model using these transition variables is presented in Figure 3.6.

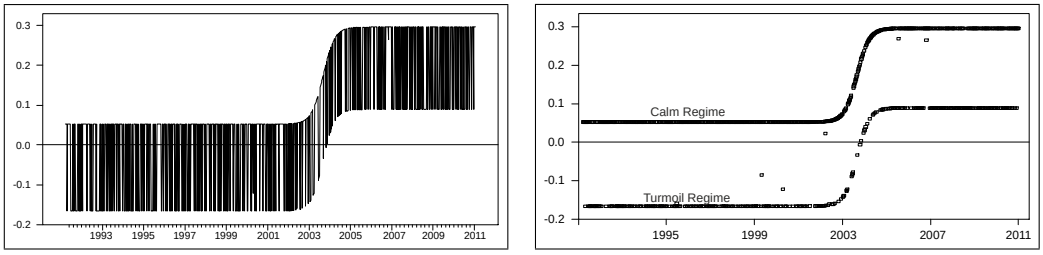


Figure 3.6: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of Shgh-A

The transition from low levels to high levels with respect to first transition variable, calendar time, is relatively slow and starts at the beginning of 2003 and settles down towards the middle of 2004[15]. Before 2003, the conditional correlation takes on the value of either 0.052 or -0.166 and after mid-2004 it is either 0.089 or 0.296 with respect to value of second transition variable, second lag of absolute value of standardized error of Shgh-A. The speed of transition with respect to second transition variable is very fast ($\gamma_2 = 400$). Thus there is no transition period and correlation regimes can be identified according to whether the transition variable is above or below the threshold value.

When second transition variable is less than its threshold value of 0.8, or in other words, when the volatility in Shgh-A is low, the conditional correlation is said to be in the calm regime and it smoothly increases from 0.052 to 0.296 as indicated along the upper line in the graphs of Figure 3.6. When the volatility is relatively high (above the 0.8) the conditional correlation is in the turmoil regime and smoothly increases from -0.166 to 0.089, lower line in Figure 3.6. Thus, there is an increasing trend in both regimes and through time low correlation levels are associated with turmoil periods. These dynamics are clearer in the second graph of Figure 3.6 which depicts the scatter plot of conditional correlation to the first transition variable; time. Through time, the response of conditional correlation to the second transition variable stays same and during volatile periods of Shgh-A index the correlation is at low levels.

[15]The midpoint of transition is August, 2003.

Although global volatility does not appear among the significant transition variables (Table 3.3) in STCC-GARCH modeling, first lag of VIX become significant (Table 3.6) after controlling conditional correlation for time trend. The estimation results of DSTCC-GARCH model with transition variables of time and first lag of VIX are reported in Table 3.8 and implied conditional correlation is depicted in Figure 3.7.

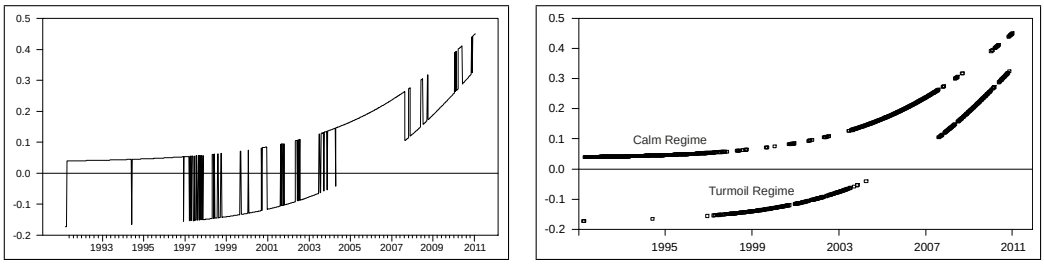


Figure 3.7: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of VIX

The speed of transition with respect to time transition variable is very slow relative to other successful DSTCC-GARCH models. The conditional correlation starts to increase in as early as 1997 and the transition period has not settled down yet. Therefore, through time conditional correlation equals to linear combination of regime specific correlations. When second transition variable, first lag of VIX, is less than its threshold value, 20.23, the correlation is in the calm regime and smoothly increases from 0.035 to 1. But since the transition with respect to time is still in progress, the conditional correlation has not reached to unity. Its highest level is 0.451 during global tranquil periods. Similarly, in turmoil regime ($s_{2t} > 20.23$) the conditional correlation smoothly increases from -0.177 to 1 but it has not attained this level, its highest value is 0.324. The upper and lower lines in the second graph of Figure 3.7 correspond to calm and turmoil regimes respectively. Therefore, during the whole period, conditional correlation shifts down to lower values in high volatile times. The conditional correlations specific to calm and turmoil regimes has been converging through time and the magnitude of the response of conditional correlation to global volatility has been decreasing.

As another second significant transition variable, first lag of standardized error of Shgh-A, delivers a competing model to the first model. The conditional correlation between Shgh-A and S&P500 from the second DSTCC-GARCH model which employs time and first lag of standardized error of Shgh-A as transition variables is depicted in Figure 3.8. The transition with respect to time variable is slower relative to first model. Starting earlier (in 2002) and ending later (in 2009), it takes more time[16]. Before 2002, the conditional correlation is either -0.149 or 0.128, and after

[16]The midpoint of transition is July, 2005.

2009 it fluctuates between 0.202 and 0.312 according to the value of the second transition variable. During transition period (between 2002 and 2009) the conditional correlation is a linear combination of regime specific constant correlations.

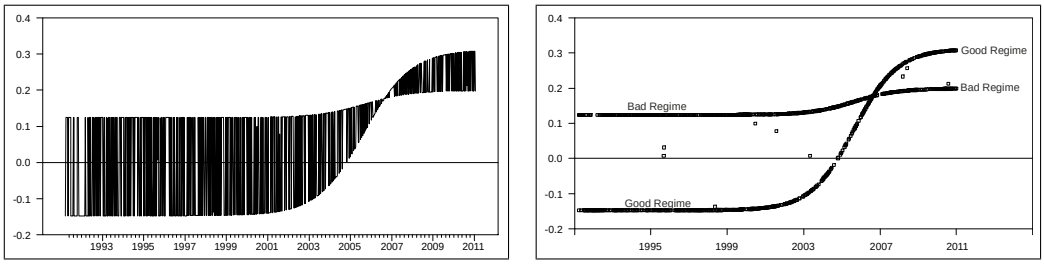


Figure 3.8: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of standardized error of Shgh-A

Like first model, the transition occur abruptly at very high speed ($\gamma_2 = 400$) with respect to the second transition variable and there is no transition period. The midpoint of transition is observed at the estimated threshold value of 0.005, thus, the sign of the error determines the regime switches. When transition variable is less (greater) than 0.005, the correlation is in the bad (good) regime which represents the response of conditional correlation to bad (good) domestic news. Through time the conditional correlation increased from 0.128 to 0.202 and from -0.149 to 0.312 smoothly in the former and latter regimes respectively, once again depicting increasing trend in both states.

An important fact revealed by Figure 3.8 is that during whole period low or high correlation levels are not specific to good or bad regime determined by the second transition variable. There is a structural change in the respond of conditional correlation with respect to news from Shgh-A in 2006. Up to this year, the conditional correlation shifts up to higher correlation (from -0.149 to 0.128) when bad domestic news appears. After this year, instead of increasing, the conditional correlation shifts down to lower levels (from 0.312 to 0.202) when bad domestic news reveals. This change may be attributed possibly to foreign investor starting to trade in A-shares and/or the other structural reforms that took place in Chinese financial markets.

The finding of structural change with respect to the first lag of standardized error of Shgh-A may provide an answer to the failure of literature in finding evidence of upward trend in conditional correlation among Shgh-A and S&P500. Since the widely used DCC-GARCH model employs standardized errors in the correlation equations and do not take structural change[17] in to account, they failed to detect an

[17] Cappiello et al. (2006) aim to detect structural change with dummy variables and they apply asymmetric model which can identify the differences between positive and negative standardized

evidence of increasing trend. On the other hand, the modeling cycle followed in this chapter implicitly covers the possibility that there can be change in the dynamics of correlation with respect to standardized error or any other transition variable without imposing any restriction on the regime specific correlation parameters and hence the model is able to capture the increasing trend with structural breaks. This structural change with respect to standardized error of Shgh-A also can help to explain why this variable rejects CCC hypothesis with low LM statistics. The LM statistics employ linear approximation, so the effects of this variable on conditional correlation diminish.

Finally, the effects of news from S&P500 on the estimated conditional correlation are plotted in the Figure 3.9. Similar to second model, bad regime is defined when the first lag of standardized error of S&P500 is less than threshold value of -0.087 or when bad news arrive from S&P500.

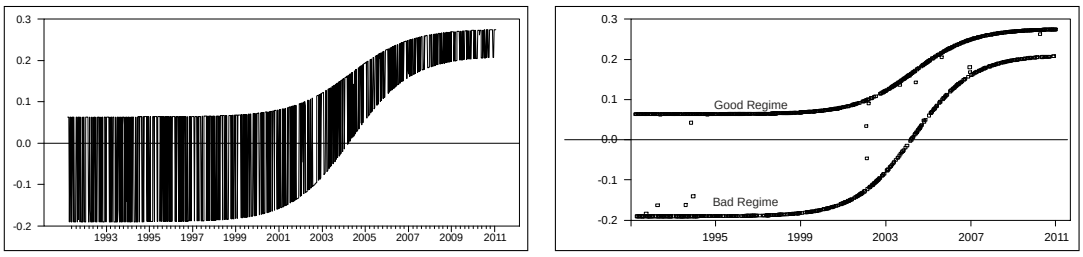


Figure 3.9: The conditional correlation between Shgh-A and S&P500 from the DSTCC-GARCH model with time and first lag of standardized error of S&P500

Through time, the transition to the higher correlation levels starts in 2001 and ends in 2008[18]. During this transition period, the conditional correlations have increased smoothly from -0.19 to 0.21 and from 0.063 to 0.275 in the bad and good regimes respectively. At first glance, the results seem to be similar with the results of the second DSTCC-GARCH model employing time and first lag of standardized error of Shgh-A but with very important difference: low correlation levels corresponds to bad regimes for both before and after the transition to higher correlation levels for whole period. With the structural change in 2006 this important difference vanishes and the conditional correlation starts to give same response to news from both Shgh-A and S&P500; the correlation level declines when a bad news appears.

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error. However their estimation results are not satisfactory when they use dummy for both intercept and slope parameters, so they use dummy for only intercept term which can detect shift in mean of conditional correlation. Even if they used slope dummy variable they could not identify the structural change in the case of non-zero threshold value.

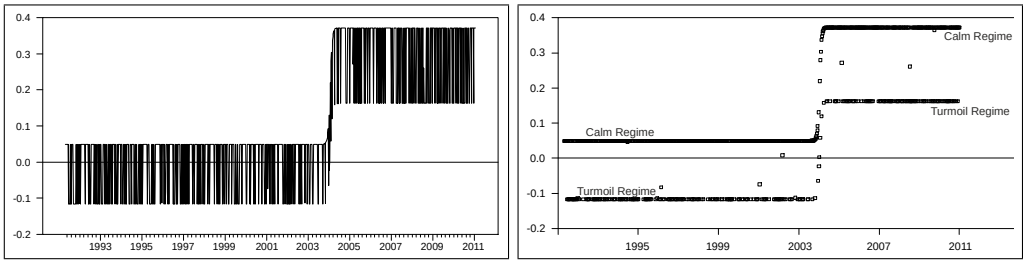
[18]The midpoint of transition is April, 2004.

The low levels of conditional correlation following bad news from S&P500 implies that Shgh-A has offered valuable opportunities to reduce risk in terms of international portfolio diversification to the US investors in times of decline in the US stock markets since July 2003 when authorized foreign investors are allowed trading in A-shares.

Figures 3.8 and 3.9 revealed another important result that before 2002 the conditional correlation between Shgh-A and S&P500 fluctuates in a wider range relative to post 2002 period with respect to the sign of the new information from both China and the US. Thus, following the foreign investors' entry in mid-2003 and structural reforms, which take place between 2001 and 2006, the magnitudes of reaction to the arrival of news had reduced to nearly one third and became insignificant after 2009. Thus, the role of news from Shgh-A and S&P500 in explaining correlation dynamics seem to lose its importance since 2009.

To sum up, the estimation results of the best DSTCC-GARCH models uncover that the conditional correlation between Shgh-A and S&P500 on average fluctuates between 0.052 and -0.166 before 2002, and 0.089 and 0.296 since then. Therefore, the implied zero correlation before 2002 and 0.214 after this date by STCC-GARCH model may be considered as the average values of correlations for their respective states (-0.166 and 0.052 ; 0.089 and 0.296) if the model is not controlled for the second transition variable.

3.3.2.2.2 Shgh-A – FTSE: Similar to Shgh-A – S&P500 case, as a second transition variable, the same volatility measure of Shgh-A, second lag of absolute value of standardized error of Shgh-A, rejects the null hypothesis of STCC-GARCH model with time transition variable. The conditional correlation between Shgh-A and FTSE implied by the first DSTCC-GARCH model with time and this second transition variable is depicted in the upper graphs of Figure 3.10. The speeds of transition are very high with respect to both transition variables, thus conditional correlation is equal to one of the four regime specific conditional correlations throughout the whole period. The switch to the higher correlation levels takes place in December 2003. The conditional correlation takes value of either -0.119 or 0.04 before this date and since then, it fluctuates between 0.126 and 0.337. Through time the conditional correlation shifts down to lower levels during volatile periods of Shgh-A. Although this second transition variable generates almost same conditional correlation dynamics for Shgh-A – S&P500 and Shgh-A – FTSE pairs, the threshold value (0.8) which identifies the calm and turmoil regimes is lower for former pair compared to the value of latter pair which is 1.058 suggesting that S&P500 is more sensitive to volatility increases in Shgh-A compared to FTSE.



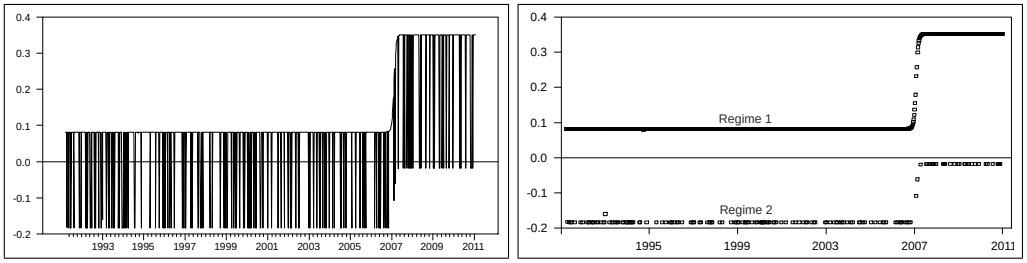


Figure 3.10: The conditional correlations between Shgh-A and FTSE from the DSTCC-GARCH models with time and stated second transition variables.

The second DSTCC-GARCH model which uses time and the fourth lag of standardized error of Shgh-A implies very comparable conditional correlation patterns to the first model. The estimated threshold value for the second transition variable, which is a measure of good and bad news, is different than zero and therefore does not allow identification of specific regimes as good and bad. As it can be seen in lower graphs of Figure 3.10, when the fourth lag of standardized error is less than threshold value, -0.428, the correlation jumps from -0.087 to 0.122 and when it is above the correlation rises from 0.048 to 0.372 at the beginning of 2004. Before this year, the conditional correlation fluctuates between -0.087 and 0.048, and since then it fluctuates between 0.122 and 0.372. Both pre-2004 and post-2004 periods the conditional correlation shifts to lower regime when things start to worsen in Shgh-A. Unlike Shgh-A – S&P500 pair, the effects of news from Shgh-A does not die out. Instead, it preserves its importance.

The STCC-GARCH model with time transition variable indicates that there is no significant correlation between Shgh-A and FTSE until the beginning of 2004. However, before this date, the DSTCC-GARCH estimates indicate that the conditional correlation moves on average between -0.1 and 0.044. Once again, the zero correlation before 2004 and the correlation level of 0.261 after this date implied by STCC-GARCH model may be thought as the average value of regime specific correlation of DSTCC-GARCH model through time.

Table 3.9: The estimation results of DSTCC-GARCH models for Shgh-B

Shgh-B – S&P500											
Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
Time + A[err.Jap]-L3	-4768.38	-0.029	-0.057	0.841^a	0.111	8.97	400	0.899^b	1.77^a	1.539	8.521^a
		(0.070)	(0.08)	(1.29)	(0.425)	(13.3)	-	(0.359)	(0.03)	[0.215]	[0.003]
Time + Time	-4769.99	-0.08	0.074^b	-	0.465^a	400	400	0.436^a	0.912^a	5.158^b	15.278^a
		(0.055)	(0.044)	-	(0.092)	-	-	(0.008)	(0.005)	[0.023]	[0.000]
Shgh-B – FTSE											
Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
A[err.UK]-L2+serr.HK-L2	-4766.77	0.062	-0.309^a	0.298^a	0.116	400	400	1.27^a	0.59^a	11.86^a	2.064
		(0.044)	(0.109)	(0.046)	(0.105)	-	-	(0.024)	(0.009)	[0.000]	[0.151]
A[err.UK]-L2+serr.US-L2	-4770.69	0.066	-0.198^c	0.273^a	0.294^a	400	400	1.68^a	0.744^a	6.741^a	0.124
		(0.043)	(0.107)	(0.056)	(0.10)	-	-	(0.038)	(0.017)	[0.009]	[0.725]
A[err.UK]-L2+S[serr.US]-L2	-4770.58	0.061	-0.111^a	0.171^a	0.312^a	400	400	1.266^a	0.549^a	4.93^b	2.028
		(0.059)	(0.007)	(0.048)	(0.022)	-	-	(0.016)	(0.01)	[0.026]	[0.154]
A[err.UK]-L2+VIX-L3	-4770.65	0.066	-0.139^b	0.284^a	0.217^a	400	400	1.27^a	21.57^a	4.43^b	1.555
		(0.046)	(0.061)	(0.057)	(0.063)	-	-	(0.012)	(0.035)	[0.035]	[0.213]
A[err.UK]-L2+A[err.Jap]-L3	-4770.11	0.117^c	-0.06	0.371^a	0.208^a	400	400	1.345^a	0.698^a	13.36^a	1.882
		(0.072	(0.055)	(0.086)	(0.057)	-	-	(0.023)	(0.05)	[0.000]	[0.17]

Table 3.9 continues

Shgh-B – CAC											
Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
A[serr.US]-L2 + Time	-4994.88	-0.044	0.315^a	0.213^a	0.522^a	400	400	1.32^a	0.735^a	13.79^a	6.343^a
		(0.043)	(0.1)	(0.062)	(0.089)	-	-	(0.01)	(0.007)	[0.000]	[0.012]
A[serr.US]-L2 + A[serr.Fr]-L1	-4996.68	-0.004	0.123^b	0.290^a	0.655^a	400	400	1.32^a	1.05^a	7.749^a	7.082^a
		(0.005)	(0.059)	(0.076)	(0.061)	-	-	(0.005)	(0.02)	[0.005]	[0.008]
A[serr.US]-L2 + A[err.Jap]-L3	-4996.53	0.062^c	-0.27^b	0.373^a	-0.622^a	400	400	1.32^a	4.71^a	8.745^a	9.061^a
		(0.036)	(0.118)	(0.074)	(0.168)	-	-	(0.008)	(0.028)	[0.003]	[0.002]
Shgh-B – Nikkei											
Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
serr.US-L2+err.Jap-L4	-5045.39	0.102	0.317^a	-0.375^a	0.069^c	400	400	-1.00^a	-3.66^a	5.836^b	28.92^a
		(0.252)	(0.077)	(0.082)	(0.039)	-	-	(0.015)	(0.195)	[0.016]	[0.000]

Notes: This table reports the estimation results of parameters in conditional correlation equation 3.4 from DSTCC-GARCH model with the stated transition variables. The mean and variance equations are given by 3.1 and 3.2, respectively. The last two columns report the Wald statistics to test the stated null hypothesis. Values in parenthesis and square brackets are standard errors and p-values, respectively. 400 is the upper constraint for speed parameters. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively. "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively."-Li" is the i-th lag of the particular variable."Ch", "US", "UK", "Fr", "Jap" and "HK" represent Shgh-B, S&P500, FTSE, CAC, Nikkei and HSI indices.

3.3.2.2.3 Shgh-A – CAC: As in S&P500 and FTSE cases, the second lag of absolute value of standardized error of Shgh-A is one of the significant second transition variable (Table 3.6) and like S&P500 case, this transition variable with time variable generates the best DSTCC-GARCH model for Shgh-A – CAC. The dynamics of estimated conditional correlation is very similar to FTSE and S&P500 cases as depicted in Figure 3.11.

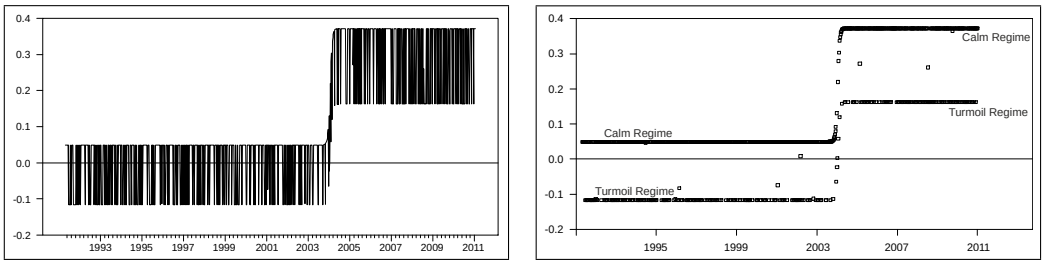


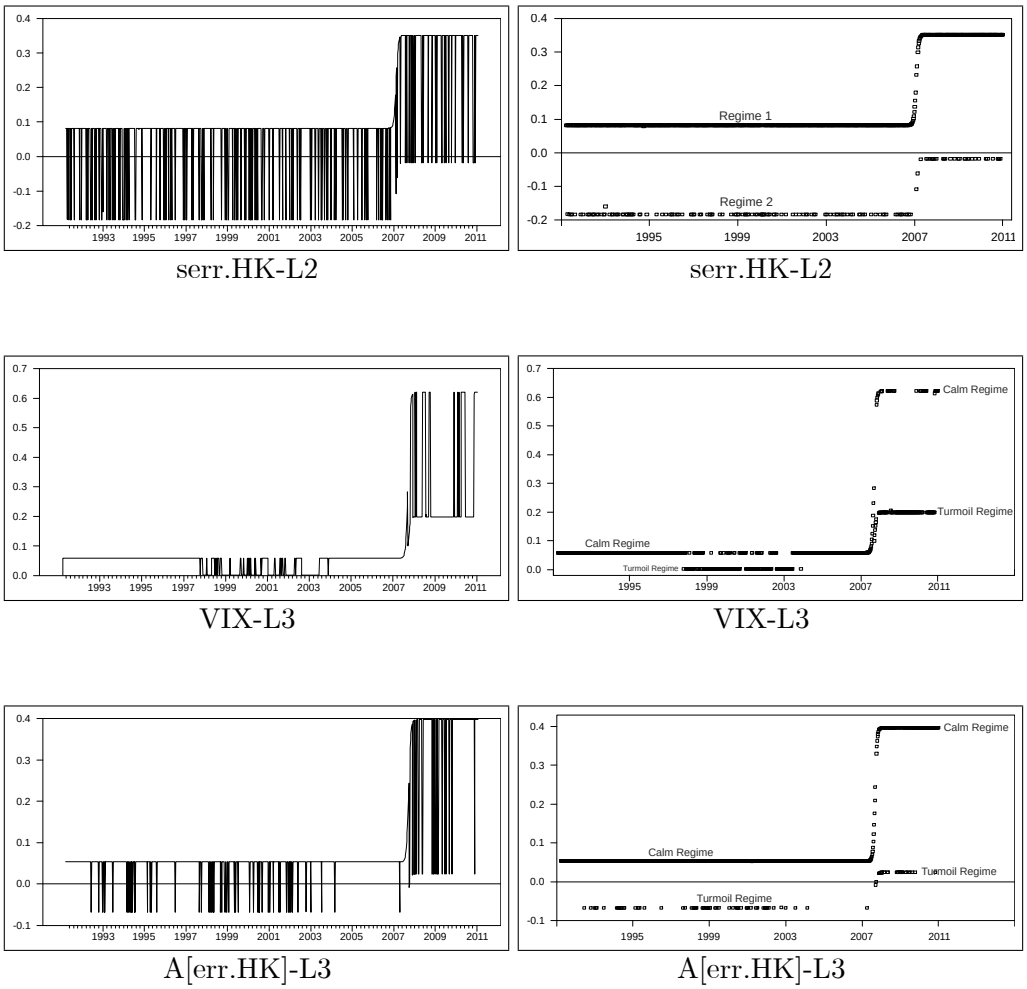
Figure 3.11: The conditional correlation between Shgh-A and CAC from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of Shgh-A

The transitions to the higher correlation levels occur abruptly at the end of 2003. The conditional correlation fluctuates between -0.116 and 0.05, and 0.162 and 0.372 before and after 2004 respectively. Similar to S&P500 and FTSE cases, the conditional correlation shifts down to lower levels during volatile periods of Shgh-A. The only difference is the threshold value which determines the calm and turmoil regimes. The CAC is more (less) sensitive to rise in volatility of Shgh-A than FTSE (S&P500).

As in the previous cases, zero correlation before 2004 and 0.298 after 2004 captured by STCC-GARCH model with time transition variable correspond to the average values of the DSTCC-GARCH estimates, (-0.116 or 0.05) before 2004 and (0.162 or 0.372) after 2004.

3.3.2.2.4 Shgh-A – Nikkei: The conditional correlation between Shgh-A and Nikkei implied by successful DSTCC-GARCH models are depicted in Figure 3.12. The upper graphs correspond to the first DSTCC-GARCH model using time and a measure of good and bad news from HSI; second lag of standardized error of HSI. The transitions with respect to both transition variables occur very sharply. Hence the conditional correlation equals to one of the four regimes specific correlations through time and shifts up to higher levels in January 2007. Before 2007, the conditional correlation fluctuates between 0.082 and -0.184 and since then it fluctuates between -0.018 and 0.352 depending on whether second transition variable is above or below its threshold. The correlation levels of zero and 0.315 implied by STCC-GARCH

model can be interpreted as the average of these levels. The non-zero threshold value ($c_2 = 0.844$) does not permit identification of specific regimes as good and bad. In January 2007, the conditional correlation shifts up from 0.082 to 0.352 and from -0.184 to -0.018 when this transition variable is below and above its threshold value of 0.844 respectively.



serr.HK-L2 serr.HK-L2

VIX-L3 VIX-L3

A[err.HK]-L3 A[err.HK]-L3

Figure 3.12: The conditional correlations between Shgh-A and Nikkei from the DSTCC-GARCH models with time and stated second transition variables

Similar to Shgh-A – S&P500 case, global volatility is indicated as significant transition variable after controlling for time trend. As a second transition variable, using third lag of VIX index and absolute value of error of HSI in DSTCC-GARCH models indicate that up to September 2007 there is no significant correlation between Shgh-A and Nikkei. But, since then, the correlation starts to give response to these volatility measures and it is either 0.198 or 0.621 and either 0.024 or 0.397 according to former and latter additional transition variables, respectively. The second model

recognizes the values of VIX index which are greater than 21.57 as turmoil regime. In the third model, this regime is identified when the third lag of absolute value of error of HSI is greater than 5.933. In both models, low correlation levels are associated with turmoil regimes.

3.3.2.2.5 Shgh-B – S&P500: As presented in Table 3.7, two volatility measures of Nikkei, third lag of absolute value of error and third lag of square of error, are indicated as second transition variables in addition to time. The DSTCC-GARCH model using time and the former variable delivers the best fit for the conditional correlation between Shgh-B and S&P500 indices. Figure 3.13 clearly show that the conditional correlation starts to increase in 2001 with very low speed. Thus the transition to the higher levels has not settled down yet and the regime specific correlations, 0.111 and 0.841, corresponding to the higher correlation levels are not attained. Therefore, since 2000 the conditional correlation equals to linear combination of regime specific constant correlations. Before 2000, the conditional correlation is very close to zero and fluctuates between -0.029 and -0.057 depending on whether the second transition variable is greater or less than its threshold value, 1.77. During the transition period, the increasing trend in conditional correlation between Shgh-B and S&P500 is interrupted by rise in the volatility of Nikkei and correlation shifts down to lower levels if the second transition variable is above its threshold, i.e. the volatility of Nikkei is high.

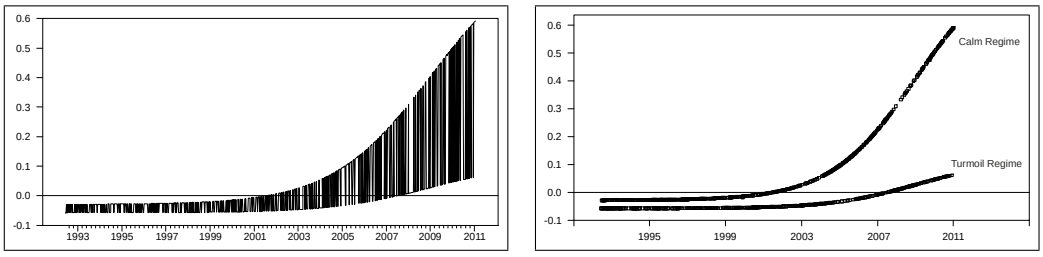


Figure 3.13: The conditional correlation between Shgh-B and S&P500 from the DSTCC-GARCH model with time and third lag of absolute value of error of Nikkei

Other successful DSTCC-GARCH model for Shgh-B and S&P500 pair is the one which uses time in both transition functions. Although ML does not select this model, the dynamics of estimated conditional correlation from DSTCC-GARCH model with time and time seem to be interesting and it is depicted in Figure 3.14. It seems that there are two important shifts in correlation through time. In the first one, correlation shifts from -0.08 to 0.074 in August 1999. The second shift took place in March 2009 and levels at 0.465 which can be thought as the average of correlations levels implied by third lag of absolute value of error of Nikkei after this date.

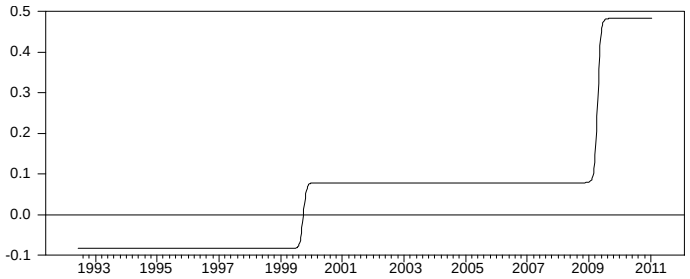


Figure 3.14: The conditional correlation between Shgh-B and S&P500 from the DSTCC-GARCH model with time and time

3.3.2.2.6 Shgh-B – FTSE: Based on the estimation results of STCC-GARCH model, the best model for the conditional correlation between Shgh-B and FTSE is not obtained with time but with the transition variable of second lag of absolute value of error of FTSE which is a measure of FTSE volatility. The STCC-GARCH estimates indicate that the conditional correlation shifts from zero to 0.259 when the volatility of FTSE increases above its threshold value of 1.343. However, since the null hypothesis of STCC-GARCH model is rejected by eight additional transition variables (see Table 3.7) requiring the estimation of DSTCC-GARCH models, these results are not able to sufficiently represent the conditional correlation dynamics. Although time variable is one of the significant transition variables in STCC specification, it is not among these significant second transition variables. Therefore increasing trend hypothesis is not valid for Shgh-B – FTSE pair.

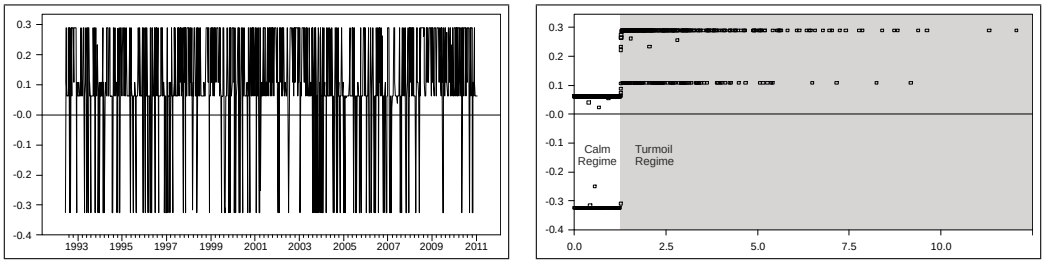


Figure 3.15: The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of HSI

DSTCC-GARCH models with all significant additional variables are estimated and the estimation results of five successful DSTCC-GARCH models are reported in Table 3.9. Among these models, the DSTCC-GARCH model with the second lag of absolute value of error of FTSE and second lag of standardized error of HSI provides the highest ML value. The conditional correlation as a function of these variables is plotted in Figure 3.15. The speeds of transitions with respect to both

transition variables are very high, so there is no transition period and conditional correlation takes on one of the values of the four regime specific correlations through time. If the second lag of absolute value of error of FTSE is less than its threshold value, 1.27 (or when the volatility of FTSE is low), the conditional correlation is 0.062 when the value of second lag of the standardized error of HSI is less than its threshold value 0.59 and it is -0.309 otherwise. Similarly, during turmoil periods of FTSE the conditional correlation is either 0.298 or 0.116 according to the value of second transition variable. Thus the conditional correlation between Shgh-B and FTSE increases with the rise in the volatility of FTSE and with the decline in standardized error in HSI. Therefore the highest correlation level, 0.298, is attained when the second lag of absolute value of error of FTSE is greater than its threshold and the second lag of the standardized error of HSI is less than its threshold.

Like news from HSI, the news from S&P500 carries significant information in explaining conditional correlation between Shgh-B and FTSE. The DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of S&P500 which is plotted in Figure 3.16, imply that during low volatility of FTSE the conditional correlation is either 0.066 if the second transition variable is less than its threshold value of 0.744 or -0.198 if it is higher.

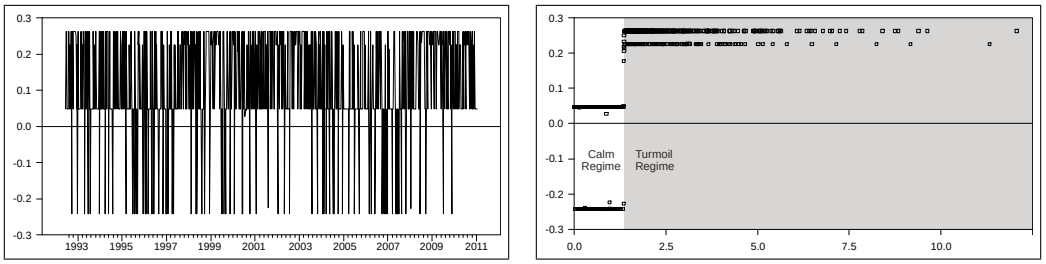


Figure 3.16: The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and second lag of standardized error of S&P500

However, during high volatile periods of FTSE, the news from S&P500 index losses its importance and conditional correlation is about 0.28. Therefore, there are three effective regimes in this case. Like the first DSTCC-GARCH model, if the volatility of FTSE rises above its threshold and standardized error of S&P500 declines below its threshold the conditional correlation shift up to higher levels.

The responses of conditional correlation between Shgh-B and FTSE to the volatility measures, second lag of square of standardized error of S&P500 and third lag of VIX, after controlling for volatility of FTSE are plotted in Figure 3.17. Since the estimated threshold values of first transition are very close (see Table 3.9; 1.266 vs. 1.27), these models' calm and turmoil regimes with respect to volatility measure

of FTSE seem to be coinciding. During low volatile periods of FTSE (when the first transition variable, second lag of absolute value of error of FTSE, is less than its threshold value) the conditional correlation is either 0.061 or -0.111 and 0.066 or -0.139 according to the volatility of S&P500 and global volatility, respectively. Similarly, it fluctuates between 0.171 and 0.312, and 0.217 and 0.284 if the volatility in FTSE is high. At first glance, it seems that these volatility measures, volatility of S&P500 and global volatility, imply almost same regime specific correlation levels. However, as it can be seen from Figure 3.17, they generate very different dynamics.

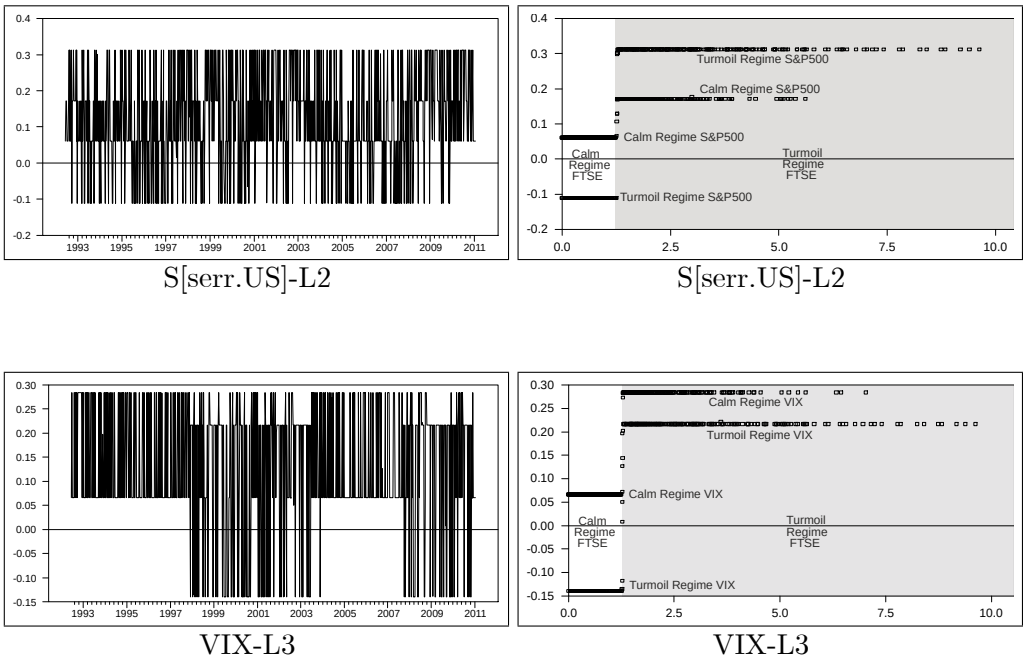


Figure 3.17: The conditional correlation between Shgh-B and FTSE from the DSTCC-GARCH model with second lag of absolute value of error of FTSE and stated second transition variables

During tranquil periods in both FTSE and S&P500 the correlation is very close to zero but when the volatility of S&P500 rises above its threshold value, 0.549, the correlation decline to -0.111. On the other hand, a rise in the volatility of S&P500 beyond its threshold leads to an increase in conditional correlation from 0.171 to 0.312 during high volatile times in FTSE. Thus the highest correlation level is attained during turmoil periods in both FTSE and S&P500. Unlike volatility of S&P500, global volatility leads to a decrease in conditional correlation independent of the state of the FTSE.

3.3.2.2.7 Shgh-B – CAC: A volatility measure of S&P500, second lag of absolute value of standardized error, delivers the best STCC-GARCH specification for Shgh-B – CAC pair (Table 3.5) and the estimation results show that the conditional

correlation is very close to zero if the volatility in S&P500 is low. But when the volatility rises above its threshold, 1.32, the correlation shifts up to 0.37. For this pair, time variable, which is one of the significant transition variables in STCC modeling, appears among the significant second transition variables in addition to the best first transition variable and produces the best DSTCC-GARCH model. Thus, increasing trend in conditional correlation is also valid for Shgh-B – CAC case. The conditional correlation between Shgh-B and CAC implied by these transition variables are presented in Figure 3.18.

The transition to higher correlation levels takes place in August 2005. Up to this date, the conditional correlation is around zero if the volatility of S&P500 is low or in other words if the second lag of absolute value of standardized error of S&P500 is below its threshold, 1.32, but it increases to 0.315 during turmoil periods. After 2006 it is 0.213 during calm times and shifts up to 0.522 when the volatility increases. Both before and after the transition the conditional correlations move to higher levels when the volatility of S&P500 rises.

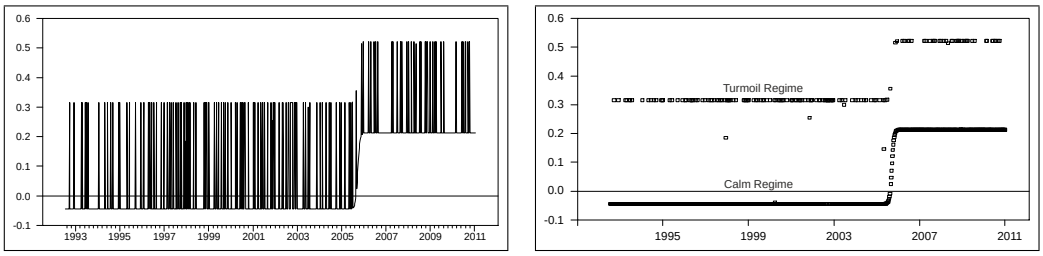


Figure 3.18: The conditional correlation between Shgh-B and CAC from the DSTCC-GARCH model with time and second lag of absolute value of standardized error of S&P500

3.3.2.2.8 Shgh-B – Nikkei: Like FTSE and CAC cases, the best STCC-GARCH model is obtained by using transition variable other than time variable. The second lag of standardized error of S&P500 is selected as the optimal transition variable in STCC-GARCH model and defines two regime specific correlations, 0.327 and 0.033. The conditional correlation is 0.327 if this transition variable is less than its threshold, -1.27. But it is very close to zero if the standardized error is greater than this value. The null hypothesis of STCC-GARCH model is rejected by three additional transition variables (Table 3.7). The only successful DSTCC-GARCH model which is reported in Table 3.9 employs second lag of standardized error of S&P500 and fourth lag error of Nikkei. The threshold values of both transition variables are non-zero obscuring regime identifications as good and bad, and the conditional correlation between Nikkei and Shgh-B is governed by three effective regimes. As Figure 3.19 clearly indicates, the conditional correlation is -0.375 if the fourth lag of

error of Nikkei is less than its threshold[19], -3.66, and it is either 0.069 or 0.317 if it is greater.

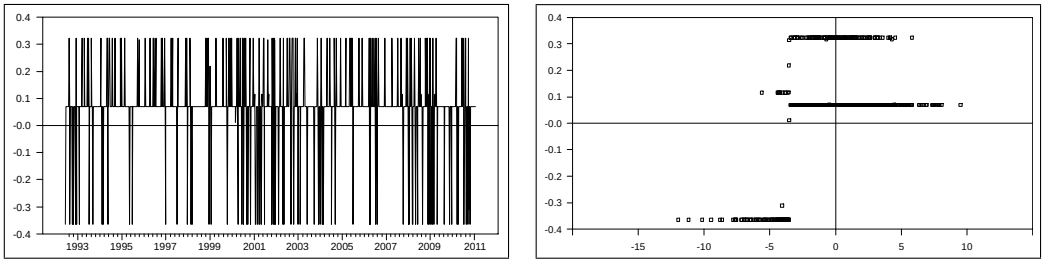


Figure 3.19: The conditional correlation between Shgh-B and Nikkei from the DSTCC-GARCH model with second lag of standardized error of S&P500 and fourth lag error of Nikkei

Similar to STCC specification, this best DSTCC-GARCH model indicates that when the first transition variable, second lag of standardized error of S&P500, is below its threshold the conditional correlation equals to 0.317. However, unlike STCC, when the first transition variable is greater than its threshold, conditional correlation takes on two values (-0.375 and 0.069) whose average value (0.033) is given by STCC specification.

3.3.2.3 Comparison of Models

To compare the performance of STCC-GARCH and DSTCC-GARCH models, AIC and SIC information criteria are calculated and reported with ML values in Table 3.10. The highlighted figures in AIC and SIC columns represent better specification of conditional correlation. For all index pairs, additional transition function improves the log-likelihood value as expected and DSTCC-GARCH models are selected by AIC. However SIC which penalizes the number of parameters more strongly identifies single transition as superior representation of the conditional correlation. Although DSTCC-GARCH models do not preferred by SIC, these models enable us to discover the role of factors such as global volatility, index specific volatility and type of news from indices in the dynamic nature of conditional correlations.

3.4 Conclusion

In order to address the question of whether China can provide opportunities to reduce risk levels born by international investors via international portfolio diversification, this Chapter investigates the dynamic structure of return correlation between stock market in China and stock markets in the US, UK, France and Japan. The

[19] In fact, it is either 0.102 or -0.375 when the fourth lag of error of Nikkei is less than its threshold. But there are only ten values equal to 0.102, making regime identification implausible.

Table 3.10: Values of log-likelihood and information criteria

		Shgh-A			
	Model	Transition Variable(s)	ML Value	AIC	SIC
S&P500	STCC	Time	-4935.216	9.978	10.047
	DSTCC	Time + A[serr.Ch]-L2	-4929.478	9.975	10.064
		Time + serr.Ch-L1	-4929.492	9.975	10.064
		Time + serr.US-L1	-4930.158	9.976	10.065
		Time + VIX-L1	-4930.462	9.977	10.066
FTSE	STCC	Time	-4940.482	9.989	10.058
	DSTCC	Time + A[serr.Ch]-L2	-4936.814	9.990	10.078
		Time + serr.Ch-L4	-4935.801	9.988	10.076
CAC	STCC	Time	-5169.494	10.453	10.527
	DSTCC	Time + A[serr.Ch]-L2	-5165.291	10.452	10.546
Nikkei	STCC	Time	-5234.209	10.581	10.650
	DSTCC	Time + serr.HK-L2	-5228.582	10.578	10.667
		Time + VIX-L3	-5228.866	10.578	10.667
		Time + A[err.HK]-L3	-5231.045	10.583	10.672
		Shgh-B			
	Model	Transition Variable(s)	ML Value	AIC	SIC
S&P500	STCC	Time	-4773.28	9.654	9.728
	DSTCC	Time + A[err.Jap]-L3	-4768.38	9.652	9.746
		Time + Time	-4769.99	9.653	9.742
FTSE	STCC	A[err.UK]-L2	-4773.26	9.654	9.728
	DSTCC	A[err.UK]-L2 + serr.HK-L2	-4766.77	9.649	9.743
		A[err.UK]-L2 + serr.US-L2	-4770.69	9.657	9.750
		A[err.UK]-L2+S[serr.US]-L2	-4770.58	9.656	9.750
		A[err.UK]-L2 + VIX-L3	-4770.65	9.657	9.750
CAC	STCC	A[serr.US]-L2	-5001.47	10.116	10.195
	DSTCC	A[serr.US]-L2 + Time	-4994.88	10.111	10.209
		A[serr.US]-L2+A[serr.Fr]-L1	-4996.68	10.114	10.213
		A[serr.US]-L2+A[err.Jap]-L3	-4996.53	10.114	10.223
Nikkei	STCC	serr.US-L2	-5054.04	10.220	10.294
	DSTCC	serr.US-L2 + serr.Jap-L4	-5045.39	10.210	10.304

analysis covers the both A-share and B-share indices in Shanghai Securities Exchange (Shgh-A and Shgh-B). The first aim is to seek for an evidence of increasing trend, which is expected as a result of reforms in Chinese financial markets but has not been found, in the conditional correlation of both Shgh-A and Shgh-B indices with S&P500, FTSE, CAC and Nikkei indices. The second one is to reveal the structure and the properties of correlation with respect to global volatility, index specific volatility and the sign of the news from the indices whose effects on the dynamic nature of conditional correlation is of interest for a long time in the literature. To incorporate the fact that the conditional correlations among international stock markets are time varying, the conditional correlations between stock market indices are modeled in the context of multivariate GARCH (MGARCH) models with time varying conditional correlations by using smooth transition conditional correlation (STCC-GARCH) and double smooth transition conditional correlation (DSTCC-GARCH) models proposed by Silvennoinen and Teräsvirta (2005 and 2009).

Unlike earlier literature, the estimation results reveal evidence of increasing trends in the conditional correlations of Shgh-A index with S&P500, FTSE, CAC and Nikkei indices and Shgh-B with S&P500 and CAC. But, for Shgh-B – FTSE and Shgh-B – Nikkei pairs, evidence of increasing trend cannot be identified. The starting years of transition range from 2002 to 2007. Therefore it can be concluded that the structural reforms and liberalization policies since 1999 and the regulations take place between 2001 and 2006 following the commitments made by China during its admission to the WTO in December, 2001 have headed the integration of stock markets with the rest of the world and hence increasing correlation. These findings imply that the opportunities offered by Shanghai stock market in China have been decreasing since 2002.

Before the transition to the higher levels, the conditional correlations are very close to zero for all index pairs. However, since 2007 the average values of conditional correlations of Shgh-A equal to 0.21, 0.26, 0.298 and 0.315 with S&P500, FTSE, CAC and Nikkei, respectively. Besides, the DSTCC-GARCH models show that market volatility plays significant role and uncovers that volatile periods lead to lower correlation compared to calm periods of Shgh-A. The conditional correlation can reach to 0.296, 0.337 and 0.372 with S&P500, FTSE and CAC during the calm periods of Shgh-A. Similarly, it can reach to 0.621 with Nikkei during the global tranquil periods. For Shgh-B, the conditional correlation increases beyond 0.6 for S&P500 and 0.5 for CAC but it is around 0.29 for FTSE and 0.32 for Nikkei. However these correlation levels are still low relative to the correlation among developed markets and even between developed and developing markets supporting the conclusion that Chinese stock markets can still offer valuable opportunities to reduce risk.

CHAPTER 4

THE ORIGINS OF INCREASING TREND IN CORRELATIONS AMONG EUROPEAN STOCK MARKETS[1]

4.1 Introduction

The recent empirical literature analyzing the dynamic structure of correlations indicates that the correlations among financial markets have tended to increase over time. The level of correlation varies from country to country and from region to region but the highest levels are attained among developed countries in European Union (EU). The increasing correlations among EU member countries' stock markets have been reducing the potential benefit of international portfolio diversification within the EU core countries.

This result calls for seeking emerging markets in EU whose correlations with developed financial markets are low and which have potential to grow fast. Therefore the correlations among developed and emerging countries in EU are worth to be examined. To this end, Cappiello et al. (2006b) and Savva and Aslanidis (2010) study the structure of correlations among new member countries and core countries of EU. The former use regression quantile approach with daily data from January 1994 to November 2005 while the latter employ bivariate GARCH with smooth transition

[1] Materials from this chapter are presented at the 5th CSDA International Conference on Computational and Financial Econometrics (CFE'11) 17-19 December 2011, Senate House, University of London, UK.

conditional correlation model to weekly data from January 1997 to November 2008. Cappiello et al. (2006b) conclude that degree of integration of the new members with core countries has increased during their accession process. They report that there are strong return co-movements among core members and Czech Republic, Hungary and Poland, while the levels of integration of Cyprus, Estonia, Latvia and Slovenia are still very low. In addition, Savva and Aslanidis (2010) reveal evidences of upward trend in the correlation of Slovenia as well as Czech Republic and Poland.

Thus, the results imply that the attractiveness of major emerging countries in terms of international portfolio diversification in EU has declined substantially after their accession to the union. At this point an interesting research topic is that whether financial markets in Turkey which is a member candidate and which have high potential to fast economic growth with well-established economic institutions can be an alternative market for EU area in providing lower risk levels to investors.

This Chapter evaluates the potential of Turkish stock market in providing diversification benefits to international investors. To this end, the conditional correlations between stock markets in Turkey and four developed countries, the US, UK, France and Germany are modeled and their dynamic structure and properties are studied in two steps. Firstly, by using the flexibility of STCC-GARCH model, time is employed as transition variable in modeling conditional correlation to test the increasing trend hypothesis. In order to investigate whether the structure of rising trend in conditional correlations are affected by the status of being a member or being a candidate member, three of the new members joining to EU in 2004, namely Hungary, Czech Republic and Poland, and the new members in 2007, Bulgaria and Romania, are selected and the conditional correlations of stock markets in these new members of EU with the stock markets in the US and Germany are also examined via STCC-GARCH model using time transition variable. The timing of upward trends in the conditional correlations between stock markets in Turkey (which is not a member yet) and Germany are compared with the timing of those between stock markets in new members and Germany. The date of membership acceptance and the dates of transition from low correlation levels to high levels are also compared to see the possible effects of being a member on the conditional correlation. Besides, the issue of whether the changes in the conditional correlations are dominated by global factors or EU related developments is also examined. Thus, the timing of upward trends in conditional correlations of stock markets in Turkey and new members with the stock markets in Germany are compared with those of stock markets in Turkey and new members with stock market in the US. If the increase is due to EU related developments then the correlation is expected to increase to higher levels earlier with EU than with the US for all new members and Turkey. The estimation results of STCC-GARCH model with time being transition variable indicate that the upward trend is valid for conditional correlations between all country pairs and it seems that

rising trends are independent of being a member but mainly due to global factors..

Finally, to address the main purpose of this Chapter, the roles of global volatility, index specific volatility and the sign of the news from the indices in explaining the dynamic nature of conditional correlations among Turkish stock market and stock markets in the US, UK, France and Germany are investigated via STCC-GARCH and DSTCC-GARCH modeling framework by considering several measures of these factors as candidate transition variable. Empirical results imply that the conditional correlation of Turkish stock market with stock markets in EU are highly affected by volatility of Turkish stock market and tend to increase during high volatile times. On the other hand, the correlation with the stock market in the US is affected by volatility of stock markets in EU and the US. The response of the correlation to volatilities in these developed stock markets changes in October 2003. Before this date the conditional correlation tends to increase in turmoil periods and after this date it tends to decline during the turmoil periods.

4.2 Literature Survey

In the empirical literature, there is very limited number of study examining the correlation structure of Turkish stock market and Taştan (2005) is the first paper in the multivariate GARCH (MGARCH) framework[2]. He measures the degree of integration between Turkish stock market and stock markets in Germany, France, UK and the US by using scalar DCC-GARCH specification for the period from November 26, 1990 to August 20, 2004. Taştan (2005) reports that all conditional correlations among stock markets are time varying during the period under examination and the correlation of Turkish stock market with developed countries fluctuates more than the correlation among developed countries. However, evidence of increasing trend cannot be identified. In his model, Taştan (2005) implicitly assumes that the correlations between all country pairs are governed by same coefficients, thus country specific news impact and smoothing parameters are not allowed. On the other hand, Syriopoulos and Roumpis (2009) employ bivariate asymmetric DCC-GARCH model to be able to take country specific factors determining correlations in to consideration. Using weekly data from April 27, 1998 to September 10, 2007, they investigate the correlation structure of major Balkan countries, namely Romania, Bulgaria, Cyprus, Greece, Turkey and Croatia with two developed countries, Germany and the US. However, Syriopoulos and Roumpis (2009) report weak co-movements among stock markets and cannot find evidence of upward trend.

[2] With cointegration and Granger causality analysis, the long-run dependence among Turkish stock market and stock markets in EU countries is examined by Benli and Başlı (2007) and Aktar (2009).

This Chapter can be seen as the extension of Savva and Aslanidis (2010). Their analysis covering Hungary, Czech Republic, Poland, Slovakia and Slovenia is extended by adding latest members, Bulgaria and Romania, and a member candidate, Turkey. The time period is also extended to December 2010 to see the up-to-date progress. Besides, while Savva and Aslanidis (2010) consider only calendar time as a transition variable, this Chapter considers the possible effects of global volatility, index specific volatility and news from the indices whose effects on the conditional correlations are of interest in the finance literature in terms of portfolio diversification.

4.3 Data and Empirical Results

4.3.1 Data

Daily closing price data of ISX100 index in Turkey, S&P500 in the US, FTSE in UK, CAC in France, DAX in Germany, all share index in Hungary (HTX) and Poland (PTX), PX Index in Czech Republic, SOFIX index in Bulgaria and Bucharest Composite (BC) index in Romania are obtained from Global Financial Data (GFD) database. In estimation of both STCC-GARCH and DSTCC-GARCH models, to weaken the possible effects of differences in the opening hours, weekly return rates of indices are used over the period from January, 09 1997 to December 30, 2010 containing 714 weekly observations[3]. As an attempt to avoid any possible end-of-week effects, Thursday closing prices are preferred to use in calculation of continuously compounding weekly return rates. All indices are denominated in local currencies[4] to exclude the possible effects of exchange rate volatility. If the estimation of GARCH parameters requires, the extreme returns which are outside the four standard deviations confidence interval around the mean are replaced by their boundary values. This truncation also alleviates the effects of outliers on LM tests used in determining appropriate transition variables.

In order to compare the performance of stock markets, normalized[5] price series are plotted in Figure 4.1. As it can be seen, the developed countries follow very similar trends, though not same. Following the financial crisis in 2008, developed stock markets in EU and the US decline more than 50% in one year. However, since 2009 they have started to recover at different speeds. The most striking fact in Figure

[3]Due to the availability of data, the sample periods start on May, 21 1998 for Czech Republic, Poland and Romania, on November, 02 2000 for Bulgaria and on May 02, 2002 for Hungary.

[4]DAX, CAC and HTX indices are in terms of Euro.

[5]The values of price series for the first Thursday of 1997 are normalized to 1. Price series are converted to Euro. The first obserbation of price series starting later than January 1997 are normalized to the value of ISX100 at that date.

4.1 is the outstanding performance of indices in new members of Bulgaria, Romania and Czech Republic, and Turkey. In five years, between 2003 and 2008, the price of indices increase approximately 900% in Bulgaria, 650% in Romania, 450% in Turkey and 300% in Czech Republic. However during the global financial turmoil started in early 2008 these indices sharply decline. SOFIX and BC indices lose almost all their gains and ISX100 and PX indices lose 85% of their gains in one year. Similar to the effects of recent financial crisis, the effects of EU membership on SOFIX and BC indices are also very apparent. Just before their membership, these indices reach to their specific highest level and when they become members they start to follow the common trend of EU countries. After 2009, all stock markets start to recover except Bulgaria[6]. The only non-member country, Turkey, have the highest speed (three times as fast as EU average) during this recovery phase and ISX100 is the only index which reaches to pre-crisis levels.

The period between 2003 and 2008 witnessing increasing trend in price of indices can be classified as low volatile period. As Figure 4.2 exhibits, the volatility of index returns are very low between 2003 and 2008 relative to period between 1997 and 2003. However in 2008 the volatility of all indices significantly increase and stay at high levels until mid-2009. It can be said that during this financial crisis S&P500 and FTSE indices record the highest volatility levels of their own history.

Table 4.1 presents the descriptive statistics of stock market returns. As it is expected from the analysis of price series Turkish stock market has the highest mean return rate. It is almost three times higher than average of developed countries in EU and two times higher than 2004's new members of Hungary, Czech Republic and Poland. All return series are negatively skewed and have significant excess kurtosis as expected. Therefore bulk of the return rates are higher than mean return rates and high negative returns are more likely than high positive returns for all indices.

Table 4.2 reveals that sample correlations of stock markets in new member and Turkey with stock markets in EU is very close to sample correlations of these countries with the US except for Bulgaria. The unconditional correlation between the US and Bulgaria is much higher than unconditional correlation between Bulgaria and EU. The sample correlations with both EU and the US is higher for indices in 2004's new members, namely Hungary, Czech Republic and Poland than for indices in 2007's new members, Bulgaria and Romania. Turkish sample correlations with EU and the US are between 2004's and 2007's new members.

[6]In addition to Bulgaria, Greece and Spain stock markets have declined since 2009.

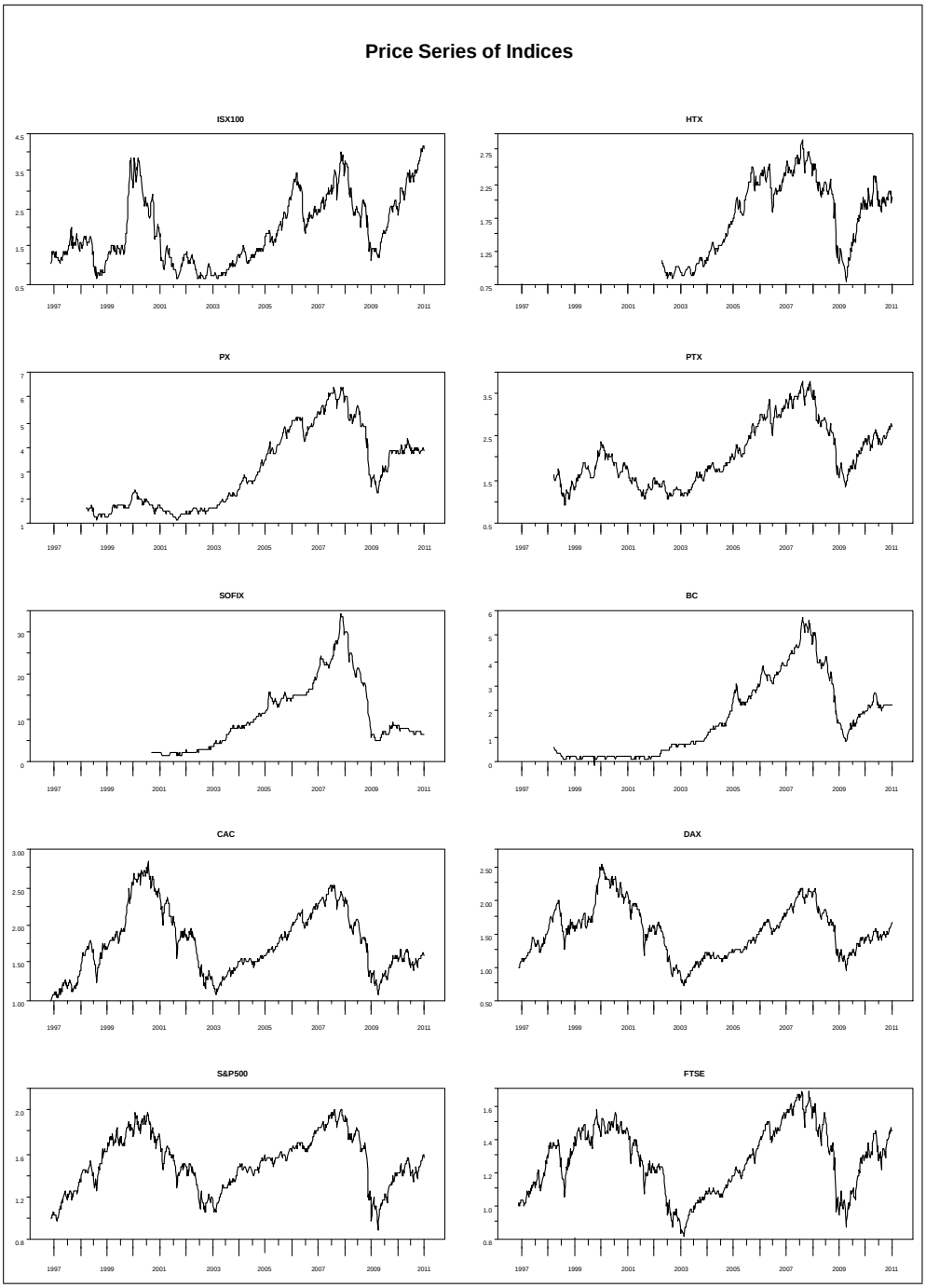


Figure 4.1: Weekly price series of ISX100 in Turkey, HTX in Hungary, PX in Czech Republic, PTX in Poland, SOFIX in Bulgaria, BC in Romania, CAC in France, DAX in Germany, S&P500 in the US and FTSE in UK

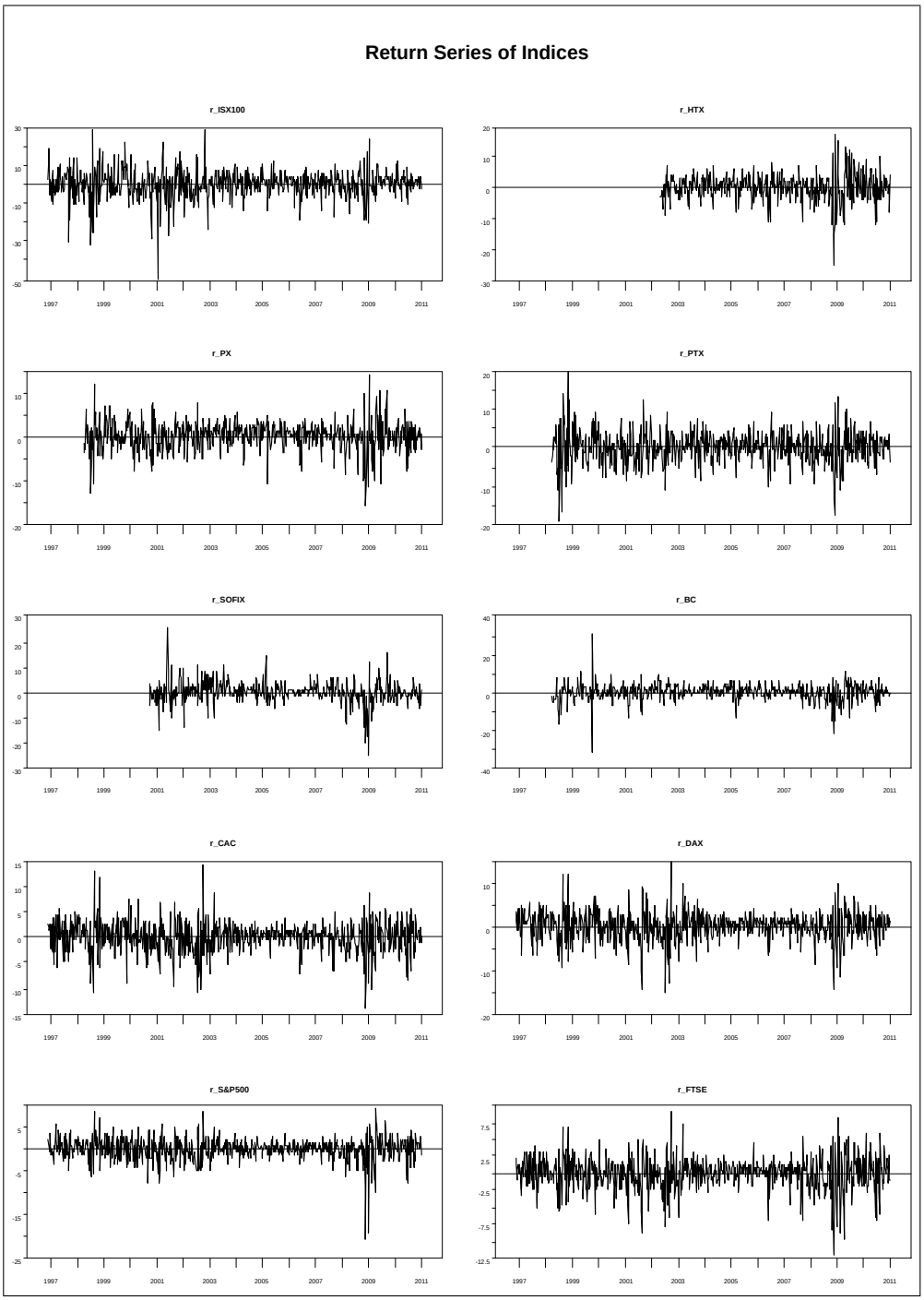


Figure 4.2: Weekly return rates of ISX100 in Turkey, HTX in Hungary, PX in Czech Republic, PTX in Poland, SOFIX in Bulgaria, BC in Romania, CAC in France, DAX in Germany, S&P500 in the US and FTSE in UK

Table 4.1: Descriptive Statistics of Return Series

	Mean	SD	Skewness	Kurtosis (excess)
CAC	0.0698	2.9270	-0.2990	2.5252
DAX	0.0893	3.1572	-0.4951	3.1130
FTSE	0.0787	2.2964	-0.6689	3.2061
S&P500	0.1287	2.4548	-1.7348	12.9784
HTX	0.1188	4.3610	-0.5058	3.9559
PX	0.0234	3.2407	-0.4883	2.6155
PTX	0.1647	4.3056	-0.0524	1.9731
SOFIX	0.2287	4.2588	-0.3454	6.8608
BC	0.1850	7.7008	-0.5623	176.3689
ISX100	0.2398	7.1764	-0.6659	4.7172

Table 4.2: Sample Correlations

	DAX	CAC	FTSE	S&P500
ISX100	0.3452	0.3329	0.3707	0.3251
HTX	0.5809	0.6127	0.6338	0.6088
PX	0.4572	0.4759	0.4957	0.4734
PTX	0.4854	0.4607	0.4797	0.4534
SOFIX	0.1980	0.2168	0.2074	0.2892
BC	0.1067	0.1384	0.1496	0.1120

4.3.2 Empirical Results

For ease of reading, mean, variance and correlation equations of STCC-GARCH and DSTCC-GARCH models are briefly summarized. The mean equation for each stock market index is formulated as autoregressive ($AR(L_i)$) process with different lag length which is enough to eliminate the linear dependence in standardized errors.

$$\begin{aligned} \text{Mean Eq.} \qquad y_{i,t} &= \mu_{i0} + \sum_{l=1}^{L_i} \mu_{il} y_{i,t-l} + u_{it} \\ u_t|\Psi_t &\sim (0, H_t) \end{aligned} \tag{4.1}$$

$$\begin{aligned} \text{Variance Eq.} \qquad H_t &= D_t R_t D_t \\ h_{ii,t} &= \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_{i1} h_{ii,t-1} \end{aligned} \tag{4.2}$$

where R_t is a 2×2 symmetric time varying conditional correlation matrix and D_t is an diagonal matrix whose diagonal elements are square root of conditional variance. Since the performance of GARCH(1,1) model is sufficient to represent many dynamics of financial time series, each element of D_t, each variance is modeled

as GARCH(1,1) process separately[7]. The conditional correlations are modeled in bivariate framework and defined as a convex combination of two(four) constant extreme correlations as a function of transition function(s) in STCC(DSTCC) model. The correlation equation of former is

$$\begin{aligned} \text{Corr Eq.} \qquad R_{ij,t} &= P_{1,ij}(1-G_t) + P_{2,ij}G_t \\ G_t &= (1+e^{-\gamma(s_t-c)})^{-1} \quad \gamma > 0 \end{aligned} \tag{4.3}$$

and the correlation equation of latter model is

$$\begin{aligned} \text{Corr Eq} \qquad R_{ij,t} &= (1-G_{2,t})[(1-G_{1,t})P_{11,ij} + G_{1,t}P_{21,ij}] \\ &\quad + G_{2,t}[(1-G_{1,t})P_{12,ij} + G_{1,t}P_{22,ij}] \end{aligned} \tag{4.4}$$

$$G_{m,t} = (1+e^{-\gamma_m(s_{m,t}-c_m)})^{-1} \quad \gamma > 0 \text{ and } m = 1,2$$

where i = ISX100, HTX, PX, PTX, SOFIX and BC
j = DAX, CAC, FTSE and S&P500

4.3.2.1 STCC-GARCH Model

As discussed, time variable is the appropriate transition variable to search for evidence of increasing trend in the conditional correlations. In line with the modeling procedure (described in the Chapter 2), the CCC null hypothesis against STCC specification with time transition variable should first be tested to avoid identification problem leading to inconsistent estimates. The LM-statistics of testing CCC hypothesis with respect to time variable are reported in Table 4.3.

Table 4.3: Test of Constant Conditional Correlation against STCC-GARCH model with Time Transition Variable

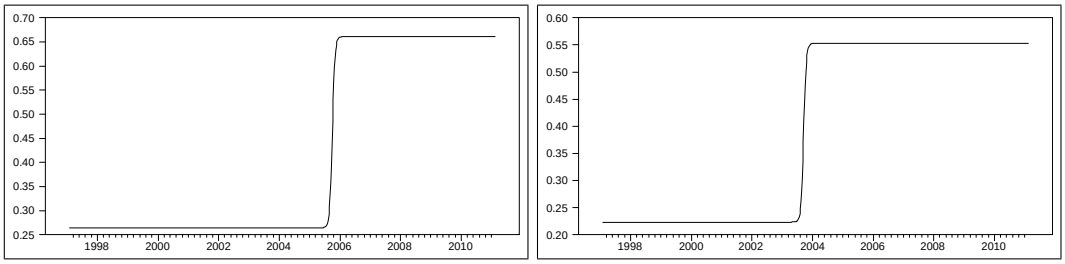
	DAX		CAC		FTSE		S&P500	
	LM-stat.	ρ-value	LM-stat.	ρ-value	LM-stat.	ρ-value	LM-stat.	ρ-value
ISX100	23.48^a	0.000	38.51^a	0.000	35.68^a	0.000	16.00^a	0.000
HTX	11.86^a	0.000	17.68^a	0.000	10.34^a	0.001	6.75^b	0.01
PX	13.87^a	0.000	14.65^a	0.000	13.34^a	0.000	11.34^a	0.000
PTX	10.20^a	0.000	10.23^a	0.000	9.38^a	0.002	4.98^a	0.025
SOFIX	22.91^a	0.000	24.09^a	0.000	23.31^a	0.000	16.97^a	0.000
BC	54.21^a	0.000	45.85^a	0.000	47.64^a	0.000	39.21^a	0.000

Notes: This table represents the LM statistic to test constant conditional correlation null hypothesis with respect to time transition variable.The LM statistics is evaluated with the estimated parameters from the restricted model of CCC reported in Appendix A.2 (see Silvennoinen and Teräsvirta, 2005). (a) and (b) denote significance at 1% and 5% levels, respectively.

[7]For SOFIX index, GARCH(2,1) eliminates the linear dependence in squared standardized errors.

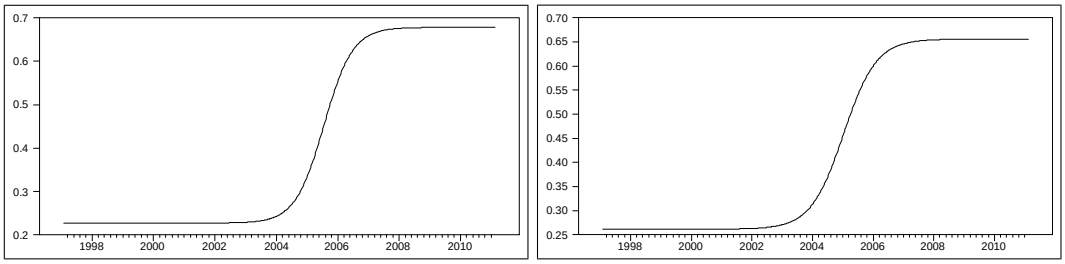
The constancy of conditional correlation is rejected for all index pairs. The strong rejection of CCC with respect to time variable means that there is a trend in each conditional correlation and the structure of these trends can be revealed by estimating the STCC-GARCH model with time transition variable. Thus, the STCC-GARCH models with time transition can consistently be estimated for all pairs and Table 4.4 presents the estimation results of conditional correlation equation for each pair[8].

The estimated conditional correlations between Turkish stock market and stock markets in Germany, France, UK and the US are plotted in Figures 4.3 and 4.4. It is clear that there are increasing trends in all conditional correlations. The conditional correlations increase considerably between the years 2003 and 2008, and as the last column of Table 4.4 indicates, these raises through time are statistically significant.



ISX100 – DAX ISX100 – S&P500

Figure 4.3: The conditional correlation of ISX100 index in Turkey with DAX and S&P500 from STCC-GARCH model with time transition variable



ISX100 – CAC ISX100 – FTSE

Figure 4.4: The conditional correlation of ISX100 with CAC and FTSE from STCC-GARCH model with time transition variable

The transitions of conditional correlations between ISX100 and DAX, and ISX100 and S&P500 to the higher levels occur sharply on their specific transition dates. For

[8]The estimation results of mean and variance equations are reported in the Appendix B.2.

Table 4.4: The estimation results of STCC-GARCH model with time transition variable

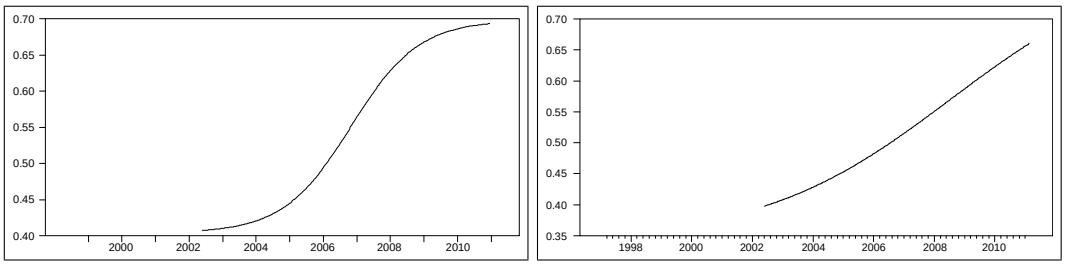
	ML-value	P_1	P_2	γ	c	H_0:P_1=P_2
ISX100-DAX	-3934.92	0.265^a	0.661^a	400	0.686^a	56.95^a
		(0.04)	(0.033)	-	(0.004)	[0.000]
ISX100-CAC	-3872.18	0.227^a	0.678^a	36.7	0.674^a	65.16^a
		(0.041)	(0.036)	(39.2)	(0.03)	[0.000]
ISX100-FTSE	-3700.26	0.261^a	0.656^a	31.6	0.643^a	47.84^a
		(0.044)	(0.034)	(23)	(0.036)	[0.000]
ISX100-S&P500	-3740.67	0.223^a	0.553^a	400	0.566^a	32.71^a
		(0.047)	(0.036)	-	(0.005)	[0.000]
HTX-DAX	-2196.76	0.404^a	0.698^a	16.91	0.756^a	6.28^b
		(0.083)	(0.071)	(14.35)	(0.071)	[0.012]
HTX-S&P500	-2078.63	0.341	0.802	5.53	0.85	0.172
		(0.457)	(0.734)	(16.3)	(0.433)	[0.679]
PX-DAX	-3129.88	0.429^a	0.655^a	400	0.691^a	24.35^a
		(0.038)	(0.031)	-	(0.007)	[0.000]
PX-S&P500	-2963.55	0.339^a	0.566^a	29.15	0.488^a	9.16^a
		(0.067)	(0.034)	(33)	(0.059)	[0.002]
PTX-DAX	-3273.83	0.477^a	0.797^a	12.21	0.848^a	1.60
		(0.044)	(0.232)	(13.92)	(0.136)	[0.206]
PTX-S&P500	-3105.25	0.446^a	0.561^a	400	0.496^a	3.53^c
		(0.053)	(0.033)	-	(0.012)	[0.060]
SOFIX-DAX	-2650.05	-0.006	0.453^a	400	0.801^a	39.90^a
		(0.061)	(0.054)	-	(0.005)	[0.000]
SOFIX-S&P500	-2502.75	-1	0.40^a	5.07^b	0.284^a	0.25^a
		-	(0.133)	(2.20)	(0.055)	[0.89]
BC-DAX	-3134.97	0.064	0.603^a	400	0.796^a	74.90^a
		(0.045)	(0.044)	-	(0.003)	[0.000]
BC-S&P500	-3161.44	-0.004	1	9.76^a	0.897^a	288^a
		(0.06)	-	(3.49)	(0.023)	[0.000]

Notes: This table reports the estimation results of parameters in conditional correlation and transition function which is described by equation 4.3 from the STCC-GARCH model with time transition variable. The mean and variance equations are given by 4.1 and 4.2, respectively. The last column reports the Wald statistics of testing the stated null hypothesis. Values in parenthesis and square brackets are standard errors and p-values, respectively. 400 is the upper constraint for speed parameters. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively.

the former pair, the conditional correlation increases from 0.265 to 0.661 in October 2005 and it increases from 0.223 to 0.553 in October 2003 for the latter (see Figure 4.3). On the other hand, transitions to the higher correlation levels are characterized by smooth transition for ISX100 – CAC and ISX100 – FTSE pairs.

The increasing trend in CAC case starts at the beginning of 2004 and settles down at the end of 2007[9]. Before 2004, the average value of conditional correlation is 0.227 and after 2008 it reaches to 0.678. For ISX – FTSE pair, the conditional correlation is 0.261 up to mid-2003 and then it starts to increase and reaches to 0.656 towards the mid-2007[10] (see Figure 4.4). Hence, when the timing of transition of conditional correlations among Turkish stock markets and stock markets in EU and the US are compared, it can be said that the co-movements between stock markets in Turkey and the US shifted to higher regime two years earlier than EU countries. Therefore the increasing trend in the conditional correlation among stock markets in Turkey and EU countries cannot solely be attributed to the EU related developments or membership process, instead the increasing correlations seem to be mainly governed by global factors. The conditional correlation shifts to higher levels earlier with S&P500 but at the end of sample, the average conditional correlation among stock markets in Turkey and EU goes beyond the correlation level between stock markets in Turkey and the US, 0.55, and reaches to 0.66. These high correlation levels considerable reduce the benefits of international portfolio diversification. However it should be mentioned that the correlation levels of Turkish stock market is still lower than the correlation among developed countries of EU which is above 0.9.

The estimated conditional correlations of stock markets in new members with DAX and S&P500 are depicted in Figures 4.5, 4.6, 4.7, 4.8 and 4.9. As can be seen, the raising trend is also valid for all new members.

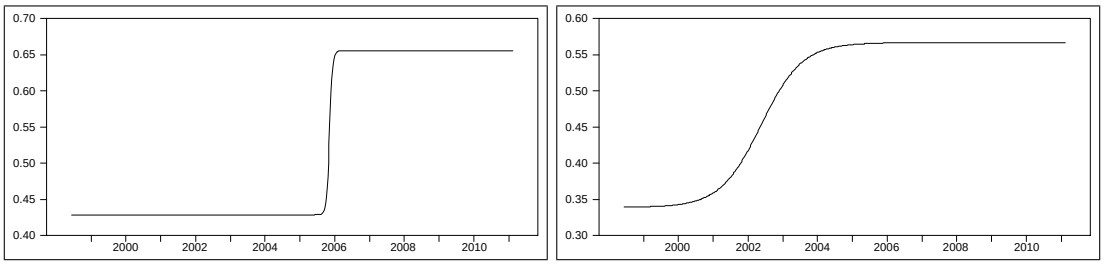


HTX – DAX HTX – S&P500

Figure 4.5: The conditional correlation of HTX index in Hungary with DAX and S&P500 from STCC-GARCH model with time transition variable

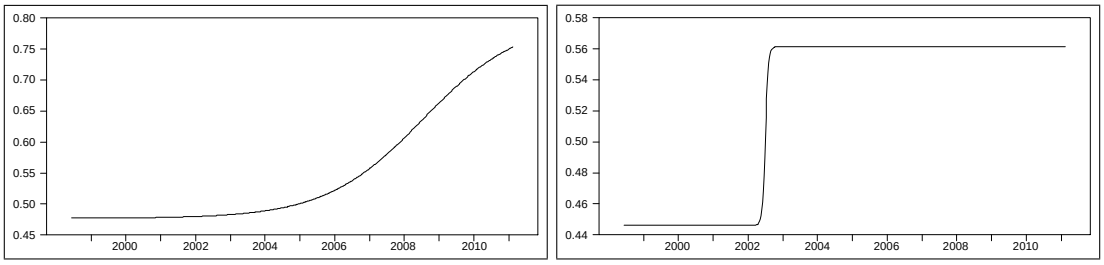
[9]The midpoint of transition is August, 2005.

[10]The midpoint of transition is January, 2005.



PX – DAX PX – S&P500

Figure 4.6: The conditional correlation of PX index in Czech Republic with DAX and S&P500 from STCC-GARCH model with time transition variable



PTX – DAX PTX – S&P500

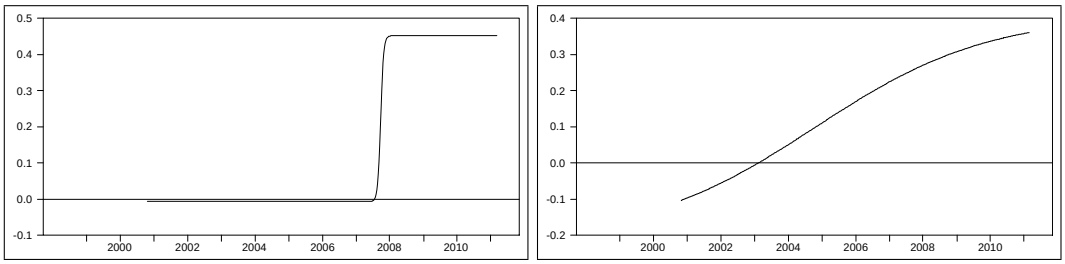
Figure 4.7: The conditional correlation of PTX index in Poland with DAX and S&P500 from STCC-GARCH model with time transition variable

The conditional correlation of HTX and PTX indices of Hungary and Poland (among 2004's new members) with the DAX increase smoothly through time. The transitions start towards the end of 2002 and the midpoints are November 2006 and June 2008, respectively. For another 2004's new member, PX index in Czech Republic, the transition to the higher levels occurs abruptly in November 2005. At end of sample period, the conditional correlation of HTX, PX, and PTX reach to the levels 0.698, 0.655 and 0.76[11] respectively.

Like PX index, the transitions of conditional correlation of SOFIX and BC indices of Bulgaria and Romania (2007's new members) with DAX are characterized by step functions. Up to the common transition date, the conditional correlations of SOFIX and BC with DAX are very close to zero and abruptly increase to 0.453 and 0.603 in August 2007 which means that the co-movements between stock market indices in Bulgaria and Germany, and Romania and Germany intensify just after their accession to EU. At the end of 2010, the level of correlation of BC reaches to those of other new members but the correlation of SOFIX stays at quite low levels

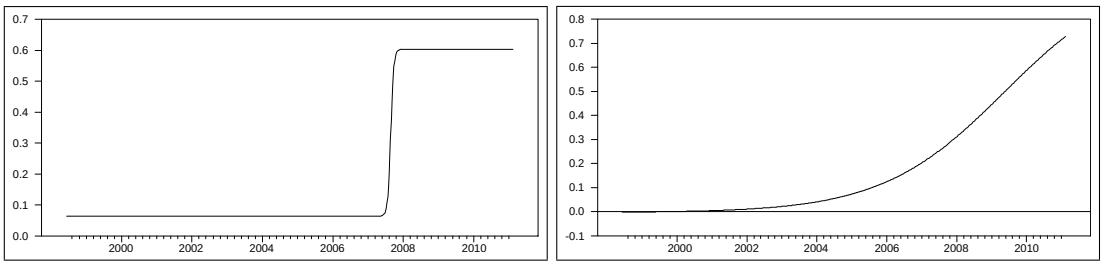
[11] The conditional correlation between PX index in Poland and DAX is still in transition at the end of 2010. Thus the regime specific constant correlation, 0.797, has not been reached yet.

relative to other new members. Unlike 2007's members (Bulgaria and Romania), the relationships between timing of increase in correlation and accession dates are not exact for 2004's members but it is seen that the transitions follow the accession progress. Therefore it can be concluded that becoming a member of EU has a significant role in the rising correlations.



SOFIX – DAX SOFIX – S&P500

Figure 4.8: The conditional correlation of SOFIX index in Bulgaria with DAX and S&P500 from STCC-GARCH model with time transition variable



BC – DAX BC – S&P500

Figure 4.9: The conditional correlation of BC index in Romania with DAX and S&P500 from STCC-GARCH model with time transition variable

To clarify the effect of EU membership status on the upward trend further, the timing of increase in conditional correlation of DAX with indices in these new members are compared with those of DAX with a index in a non-member country, Turkey. The transition date of conditional correlation between ISX100 and DAX to higher levels is between those of 2004's new members and 2007's new members. However at the end, all indices reach to the close levels of correlations with DAX except SOFIX. Therefore the estimation results imply that although Turkey has not become a member of EU yet, Turkish stock market integrated to EU as much as stock markets of new member countries which, in turn, imply that being a member cannot be playing the dominant role in the upward trend in the conditional correlation among new members and core members even though it has an important role.

Finally, the comparisons of timing of increasing trend in the conditional correlation

between new members and Germany with those between new members and the US support the previous inferences. Although it is not clear for HTX index, figures 4.5, 4.6, 4.7, 4.8 and 4.9 indicate that the conditional correlations of new members with the US start to increase earlier than with Germany as in Turkish case. However, at the end of transition the correlations level attained with the US are lower than the correlation levels attained with Germany. The transitions of conditional correlations among all indices in new members and the S&P500 start towards the mid-2001. Unlike previous comparisons, Bulgaria and Romania become more integrated with the US earlier than Turkey. Therefore the increasing trend in the conditional correlation among stock markets in new members and core countries of EU cannot solely be attributed to the EU related developments or membership process. Instead, global factors seem to mainly dominate the upward trend in the conditional correlations.

So far, the STCC-GARCH models using time as transition variable reveal that the well-documented fact in the finance literature of increasing correlation is also valid for stock markets in Turkey and new members joining in 2007, namely Bulgaria and Romania. To further elaborate the roles of factors whose effects on conditional correlation are found to be important in terms of portfolio diversification, this Chapter examines whether global volatility, index specific volatility and the sign of the news from the indices carry significant information in explaining the dynamic nature of conditional correlations among Turkish stock market and stock markets in the US, UK, France and Germany via STCC-GARCH and DSTCC-GARCH modeling framework. For this purpose, variables in all groups introduced in Section 2.4.1;VIX as a measure of global volatility, lagged conditional variance[12], lagged absolute error and lagged absolute standardized error[13], lagged squared error and lagged squared standardized errors as a measure of index specific volatility and lagged errors and lagged standardized error as a measure of the effects of good and bad news are considered with their four lags. In modeling sequence of both STCC-GARCH and DSTCC-GARCH, variables corresponding to the all indices are considered as candidate variable. This in turn produces 145 candidates for transition variables including their lags and in order to determine whether the change in conditional correlation is statistically significant with respect to these candidate variable, LM_1 test of Silvennoinen and Teräsvirta (2005) is employed for each candidate transition variable. The significant transition variables for each index pair are reported in Table 4.5.

[12] Conditional variance series are generated by univariate GARCH(1,1) model for each index separately.

[13] Errors are from GARCH(1,1) model and standardized errors are generated by dividing errors to the square root of thier conditional variance.

Table 4.5: Constant Conditional Correlation Test against Smooth Transition Conditional Correlation with one Transition Variable

ISX100 - DAX			ISX100 - CAC			ISX100 - FTSE			ISX100 - S&P500		
Transition Var	LM-stat	p-value	Transition Var	LM-stat	p-value	Transition Var	LM-stat	p-value	Transition Var	LM-stat	p-value
Time	23.48^{a}	0.000	Time	38.51^{a}	0.000	Time	35.68^{a}	0.000	Time	16.00^{a}	0.000
err.Tr-L2	4.27^{b}	0.038	serr.Tr-L2	6.03^{b}	0.014	A[err.Tr]-L4	12.78^{a}	0.000	A[err.Tr]-L4	9.26^{a}	0.002
serr.Tr-L2	7.23^{a}	0.007	A[err.Tr]-L4	26.81^{a}	0.000	S[err.Tr]-L4	11.46^{a}	0.000	S[err.Tr]-L3	15.07^{a}	0.000
A[err.Tr]-L4	14.32^{a}	0.000	S[err.Tr]-L4	24.00^{a}	0.000	A[serr.Tr]-L4	5.77^{b}	0.016	A[serr.Tr]-L4	6.57^{b}	0.010
S[err.Tr]-L4	11.14^{a}	0.000	A[serr.Tr]-L4	17.35^{a}	0.000	S[serr.Tr]-L4	5.39^{b}	0.020	A[err.Ger]-L3	14.62^{a}	0.000
A[serr.Tr]-L4	10.51^{a}	0.001	S[serr.Tr]-L4	15.11^{a}	0.000	vol.Tr-L2	5.65^{b}	0.017	S[err.Ger]-L3	21.09^{a}	0.000
S[serr.Tr]-L4	7.89^{a}	0.005	S[err.US]-L3	6.35^{b}	0.012	A[err.Ger]-L3	4.66^{b}	0.031	A[serr.Ger]-L3	12.73^{a}	0.000
A[err.Ger]-L3	5.98^{b}	0.014	A[err.Ger]-L3	4.20^{b}	0.040	S[err.Ger]-L3	11.35^{a}	0.000	S[serr.Ger]-L3	22.74^{a}	0.000
S[err.Ger]-L3	12.21^{a}	0.000	S[err.Ger]-L3	15.76^{a}	0.000	S[err.Fr]-L3	3.86^{c}	0.049	A[err.Fr]-L3	6.31^{b}	0.012
S[serr.Ger]-L3	4.43^{b}	0.035	vol.Ger-L2	5.35^{b}	0.021	A[err.UK]-L2	5.58^{b}	0.018	S[err.Fr]-L3	12.80^{a}	0.000
S[err.Fr]-L3	10.62^{a}	0.001	A[err.Fr]-L3	3.94^{b}	0.047	A[serr.UK]-L2	6.49^{b}	0.011	A[serr.Fr]-L3	17.90^{a}	0.000
A[err.UK]-L2	4.15^{a}	0.041	S[err.Fr]-L3	12.99^{a}	0.000				S[serr.Fr]-L3	15.59^{a}	0.000
vol.UK-L3	6.93^{a}	0.008	A[err.UK]-L2	6.49^{b}	0.011				A[err.UK]-L3	9.24^{a}	0.002
			A[serr.UK]-L2	7.31^{a}	0.007				S[err.UK]-L3	9.35^{a}	0.002
			vol.UK-L4	4.68^{b}	0.031				A[serr.UK]-L3	10.20^{a}	0.001
									S[serr.UK]-L3	10.14^{a}	0.001

Notes: This table represents the LM statistic to test constant conditional correlation null hypothesis with respect to particular transition variable.The LM statistics is evaluated with the estimated parameters from the restricted model of CCC reported in Appendix A.2 (see Silvennoinen and Teräsvirta, 2005). "err" and "serr" are error and standardized error from GARCH (1,1) process.S[.] and A[.] represent square and absolute value of square brackets, respectively."-Li" is the ith lag of the particular variable."Tr", "Ger", "Fr", "UK" and "US" represent ISX100, DAX, CAC, FTSE and S&P500 indices. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively.

In addition to the fact that time is a significant transition variable in describing conditional correlations of ISX100 index with DAX, CAC, FTSE and S&P500 which is indicated by Table 4.3, Table 4.5 indicates that time is the most significant transition variable which enforce the validity of the statement that conditional correlations must have time trend. It should be reminded that the indication of more than one significant transition variables by LM_1 tests may suggest the estimated STCC-GARCH models with time transition variable may be insufficient to characterize the dynamics of correlation and additional transition function with the same or different transition variable may provide better description with the estimation of DSTCC-GARCH model. Therefore the implied conditional correlations interpreted above should be considered as the average level of conditional correlations over the stated time intervals.

Test results in Table 4.5 show that other than time variable, volatility measures of ISX100, DAX, CAC and FTSE which are lagged absolute value and square of errors and standardized error of corresponding indices are common determinant of the dynamic conditional correlation between ISX100 and other indices. But volatility measure of S&P500 is indicated in only CAC case and measure of global volatility, VIX index, does not play significant role in any of the cases. Similarly, the conditional correlations of ISX100 with DAX, CAC, FTSE and S&P500 are not affected by the types of news from the latter indices. To summarize, the determinants of conditional correlation of ISX100 with

- DAX are time, two measures of type of news from ISX100 (second lag of error and standardized error of ISX100), volatility measures of ISX100 (fourth lag of absolute value of errors and standardized error, and fourth lag of squared errors and standardized error), DAX (third lag of absolute value of error, and third lag of squared error and standardized error), CAC (third lag of squared error) and FTSE (second lag of absolute value of error and third lag of conditional volatility)
- CAC are time, measures of type of news from ISX100 and volatility measures of ISX100, S&P500, DAX, CAC and FTSE
- FTSE are time and volatility measures of ISX100, DAX, CAC and FTSE
- S&P500 are time and volatility measures of ISX100, DAX, CAC and FTSE

The STCC-GARCH models can consistently be estimated with the variables reported in Table 4.5 for four index pairs. Since the LM_1 test delivers close p-values for various transition variables, STCC-GARCH models for all these transition variables are estimated and the selection of optimal one is postponed to post estimation. The results show that for all index pairs, the best fits are delivered by time variable.

Table 4.6: LM statistics of testing STCC-GARCH model with time transition variable for additional transition variables

ISX100 – DAX			ISX100 – S&P500		
Transition variable	LM-stat.	p-value	Transition variable	LM-stat.	p-value
serr.Tr-L2	4.54^b	0.033	A[serr.US]-L1	4.13^b	0.042
A[err.Tr]-L2	6.03^b	0.014	S[err.US]-L1	3.99^b	0.046
S[err.Tr]-L2	7.84^a	0.005	S[serr.US]-L1	5.47^b	0.019
vol.Tr-L1	5.73^b	0.017	err.Ger-L4	4.32^b	0.037
ISX100 – CAC			serr.Ger-L4	4.91^b	0.027
err.Tr-L2	4.32^b	0.037	A[err.Ger]-L1	3.89^b	0.048
serr.Tr-L2	4.37^b	0.036	S[err.Ger]-L1	4.33^b	0.037
A[err.Tr]-L2	7.10^a	0.008	A[serr.Ger]-L3	3.94^b	0.047
S[err.Tr]-L2	10.07^a	0.001	S[serr.Ger]-L3	5.84^b	0.016
A[serr.Tr]-L2	4.10^b	0.043	A[err.Fr]-L1	3.85^b	0.049
S[serr.Tr]-L2	6.63^b	0.010	S[err.Fr]-L1	4.58^b	0.032
ISX100 – FTSE			A[serr.Fr]-L1	4.11^b	0.043
A[err.Tr]-L2	5.09^b	0.024	S[serr.Fr]-L1	3.97^b	0.046
S[err.Tr]-L2	6.99^a	0.008	err.UK-L4	4.04^b	0.044
S[serr.Tr]-L2	5.03^b	0.025	serr.UK-L4	4.01^b	0.045
			A[err.UK]-L1	4.50^b	0.034
			S[err.UK]-L1	8.36^a	0.004
			A[serr.UK]-L3	3.94^b	0.047
			S[serr.UK]-L1	5.03^b	0.025

Notes: This table represents the LM statistics of testing estimated STCC-GARCH model with time transition variable for additional transition variables. The LM statistics is evaluated with the estimated parameters from the restricted model of STCC-GARCH model reported in Appendix B.2 (see Silvennoinen and Teräsvirta, 2009). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets, respectively."-Li" is the ith lag of the particular variable."Tr", "Ger", "Fr", "US" and "UK" represent ISX100, DAX, CAC, S&P500 and FTSE iindices. (a) and (b) denote significance at 1% and 5% levels, respectively.

Thus, time variable is selected as the optimal transition variable which enforce the reliability of the parameter estimates reported and interpreted above.

Following the modeling procedure, all estimated STCC-GARCH models are tested for additional transition variable. As in application of LM_1 test, all candidate variables in four variable groups with their lagged values are considered as candidate for additional transition variable and employed in LM_2 test of Silvennoinen and Teräsvirta (2009). If the estimated best STCC-GARCH model is not adequate to describe the correlation dynamics of the data and DSTCC-GARCH model is needed, then it is expected that LM_2 test points out the optimal transition variable for the second transition function. LM_2 test results show that any STCC specification without time transition variable is rejected in favor of DSTCC-GARCH model with time and another variable. This fact points out that time variable should be one of the

transition variables in the best DSTCC-GARCH model. The significant additional transition variables to the estimated STCC-GARCH models with time variable are presented in Table 4.6.

As seen from Table 4.6, the conditional correlations between Turkish stock market and stock markets in developed EU countries are mainly affected by information from Turkey after taking the time trend in to consideration. The news from and volatility measures of ISX100 have explanatory power over time variable. On the other hand the conditional correlation between ISX100 and S&P500 are not affected by any information about ISX100. Instead, news from EU countries and volatility measures of indices in EU and the US play significant role. The p-value columns show that significant additional transition variables reject the STCC specification with close p-values. This fact requires estimation of all possible DSTCC-GARCH models with time and all second transition variables in Table 4.6 for all index pairs and as before best model and/or transition variables selection is considered in post estimation. Since the aim is to uncover the structure of the conditional correlation with respect to factors such as index specific volatility and sign of the error represented by different variable groups, the best models within each variable group representing same dynamics are selected and the estimation results of these DSTCC-GARCH models are reported.

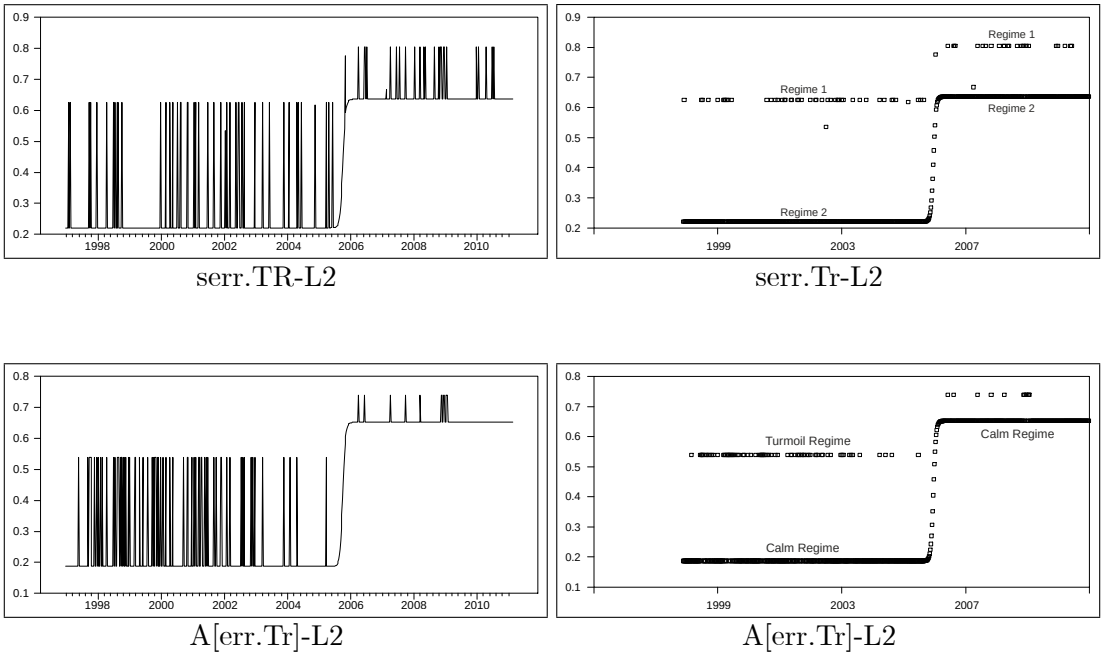
4.3.2.2 DSTCC-GARCH Model

The estimation results of conditional correlation equations of DSTCC specification corresponding to the best model within each variable group are presented in Table 4.7. The estimated conditional correlations between four index pairs are plotted and interpreted below.

4.3.2.2.1 ISX100 – DAX: There are four significant second transition variables which reject the STCC specification using time as the first transition variable for ISX100 – DAX pair. One of them is a measure of news from ISX100 and other three variables are volatility measure of ISX100. Therefore two DSTCC-GARCH models are reported; first one uses time and second lag of standardized error of ISX100 as transition variables and the second model uses time and second lag of absolute error of ISX100 which delivers the best fit among three volatility measure of ISX100. The conditional correlations implied by these two DSTCC-GARCH models are depicted in Figure 4.10.

The upper graphs visualize the effect of news from ISX100 on the conditional correlation between ISX100 and DAX. The speed of transitions with respect to both transitions variables are very high. Thus there is no transition period between specific regimes and through time the conditional correlation equals to one of the four

regime specific correlations. The transition to higher correlation levels with respect to first transition variable, calendar time, occurs abruptly in September 2005. Before this date, the conditional correlation is either 0.626 or 0.221 and since then it fluctuates between 0.805 and 0.636 according to the value of second transition variable, second lag of standardized error of ISX100 whose threshold value is -1.21. The non-zero value of threshold obscures the regime identification as good and bad regimes. When bad news which is capable of generating standardized error less than threshold value, -1.21, the conditional correlation shifts from 0.221 to 0.626 and from 0.636 to 0.805 before and after September 2005. The magnitudes of respond to the news substantially decreases following the movement to the higher correlation levels. But the difference between regime specific correlation is still significant (see last column in Table 4.7).



serr.TR-L2 serr.Tr-L2

A[err.Tr]-L2 A[err.Tr]-L2

Figure 4.10: The conditional correlation between ISX100 and DAX from DSTCC-GARCH model with time and stated transition variables.

Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
ISX100 – DAX											
Time + serr.Tr-L2	-3927.14	0.626^a	0.221^a	0.805^a	0.636^a	400	400	0.685^a	-1.21^a	55.479^a	7.201^a
		(0.029)	(0.032)	(0.049)	(0.029)	-	-	(0.011)	(0.064)	[0.000]	[0.007]
Time + A[err.Tr]-L2	-3927.42	0.187^a	0.539^a	0.652^a	0.739^a	400	307	0.685^a	8.58^a	22.578^a	0.641
		(0.044)	(0.055)	(0.03)	(0.101)	-	1614	(0.004)	(0.154)	[0.000]	[0.423]
ISX100 – CAC											
Time + err.Tr-L2	-3861.82	0.672^a	0.159^a	0.899^a	0.678^a	24.7^a	17.5^a	0.664^a	-8.86^a	14.890^a	7.047^a
		(0.042)	(0.041)	(0.058)	(0.03)	(4.46)	(2.33)	(0.022)	(0.118)	[0.000]	[0.008]
Time + A[err.Tr]-L2	-3861.30	0.145^a	0.635^a	0.681^a	0.734^a	29.4	141^a	0.661^a	9.06^a	44.716^a	0.181
		(0.044)	(0.052)	(0.035)	(0.115)	(20.5)	(35.9)	(0.029)	(0.136)	[0.000]	[0.670]
ISX100 – FTSE											
Time + A[err.Tr]-L2	-3693.09	0.185^a	0.587^a	0.649^a	0.799^a	26.4	130^a	0.626^a	9.05^a	22.906^a	3.965^b
		(0.044)	(0.061)	(0.035)	(0.065)	(16.8)	(16.2)	(0.029)	(0.024)	[0.000]	[0.046]
ISX100 – S&P500											
Time + A[serr.US]-L1	-3736.75	0.215^a	0.39^a	0.584^a	0.242	400	400	0.566^a	1.489^a	3.152^c	4.417^b
		(0.001)	(0.099)	(0.033)	(0.158)	-	-	(0.004)	(0.031)	[0.075]	[0.035]
Time + A[err.Ger]-L1	-3734.74	-0.115	0.272^a	0.677^a	0.514^a	400	400	0.566^a	0.71^a	9.384^a	6.308^b
		(0.117)	(0.044)	(0.051)	(0.045)	-	-	(0.005)	(0.02)	[0.002]	[0.012]
Time + A[serr.Fr]-L1	-3735.61	0.184^a	0.275^a	0.626^a	0.396^a	400	400	0.566^a	0.951^a	0.992	7.104^a
		(0.057)	(0.064)	(0.038)	(0.081)	-	-	(0.005)	(0.014)	[0.298]	[0.007]
Time + S[serr.UK]-L1	-3736.46	0.142^b	0.285^a	0.624^a	0.443^a	400	400	0.566^a	0.437^a	2.918^c	4.998^b
		(0.063)	(0.052)	(0.043)	(0.073)	-	-	(0.004)	(0.015)	[0.087]	[0.025]

Notes: This table reports the estimation results of parameters in conditional correlation equation 4.4 from DSTCC-GARCH model with the stated transition variables. The mean and variance equations are given by 4.1 and 4.2, respectively. The last two columns report the Wald statistics of testing the stated null hypothesis. Values in parenthesis and square brackets are standard errors and p-values, respectively. 400 is the upper constraint for speed parameters. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively. "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively."-Li" is the i-th lag of the particular variable."Tr", "Ger", "Fr", "UK" and "US" represent ISX100, DAX, CAC, FTSE and S&P500 indices.

Table 4.7: The estimation results of DSTCC-GARCH models

The lower graphs in Figure 4.10 show the response of conditional correlation between ISX100 and DAX with respect to volatility of ISX100. Similar to first model, the transitions with respect to both variables occur abruptly. Thus, the conditional correlation fluctuates between 0.187 and 0.539, and 0.652 and 0.739 before and after the transition to the higher correlation levels in September 2005. When the second transition variable, second lag of absolute error of ISX100, is less than its threshold value of 8.58, or in other words, when the volatility in ISX100 is low, the conditional correlation is said to be in the calm regime and similarly, when it is above the conditional correlation is in the turmoil regime. Through time, the conditional correlation rise to higher levels during volatile periods of ISX100 but the magnitude of increase decline and become insignificant after September 2005.

The STCC-GARCH analysis of conditional correlation between ISX100 and DAX with time transition variable uncovers that the correlation increases from 0.265 to 0.661 in October 2005. These levels can be thought as the average values of conditional correlations implied by the best DSTCC-GARCH model before September 2005 (0.626 and 0.221) and after September 2005 (0.805 and 0.636). Besides, the results of DSTCC-GARCH model indicates that the conditional correlation is able to reach 0.805 which is nearly as high as the correlations among developed countries. Therefore the attractiveness of Turkish stock market considerably diminishes in terms of international portfolio diversification.

4.3.2.2.2 ISX100 – CAC: Like DAX case, the news from ISX100 and volatility measure of ISX100 carry significant information about dynamic nature of conditional correlation between ISX100 and CAC over time trend and LM_2 test rejects the STCC-GARCH model with time in favor of six DSTCC-GARCH models which can be divided in to two groups according to their second transition variables; the first group of models employ time and a measure of news from ISX100 and the second group uses time and a volatility measure of ISX100. As a second transition variable, the second lag of error of ISX100 and the second lag of absolute error of ISX100 produce the best DSTCC-GARCH models among their groups. The estimated conditional correlations from DSTCC-GARCH models with time and second lag of error of ISX100, and time and second lag of absolute error of ISX100 are plotted in Figure 4.11.

In both models, the speed of transition with respect to time variable is relatively slow and the transition starts at the beginning of 2004 and finalizes at the end of 2007[14]. Before 2004, the conditional correlation fluctuates between 0.672 and 0.159 depending on the value of second transition variable, second lag of error of ISX100.

[14]The midpoint of transition is May, 2005.

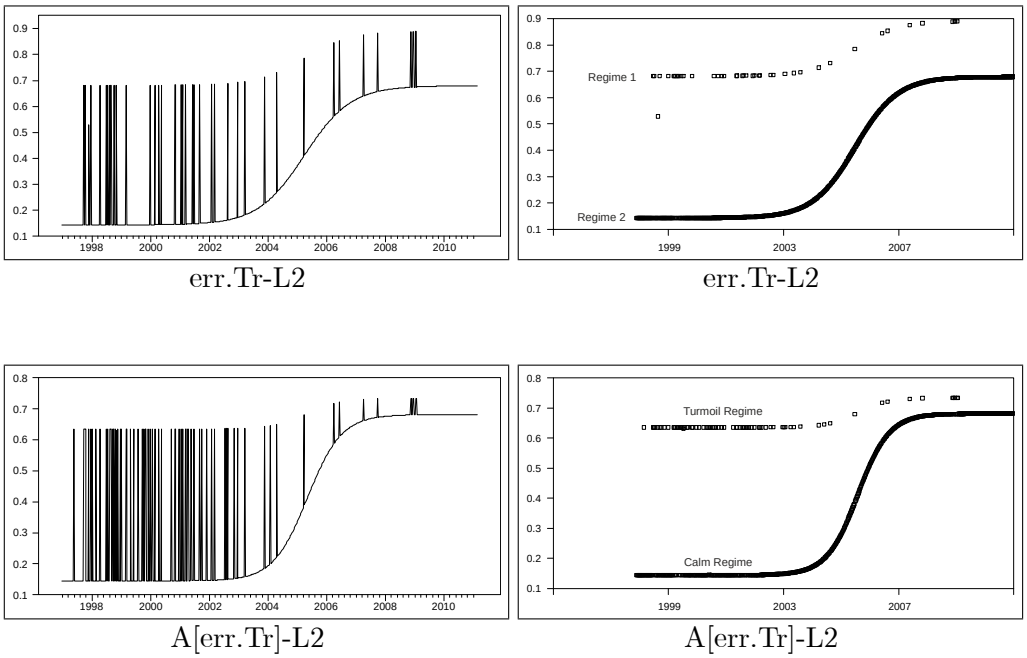


Figure 4.11: The conditional correlation between ISX100 and CAC from DSTCC-GARCH model with time and stated transition variables.

But after 2007, it is either 0.899 or 0.678 (The upper graphs in Figure 4.11). If the second transition variable is less than its threshold value, -8.86, the conditional correlation is 0.672 and 0.899 before and after the transition to the higher levels. Thus, similar to DAX case, bad news creating negative error greater than 8.86 result in higher correlation levels and response of conditional correlation to the news from ISX100 decline in magnitude after the end of transition but the difference is still significant (see Table 4.7).

The effects of volatility in ISX100 index are depicted in the lower graphs of Figure 4.11. The conditional correlation takes value of either 0.145 or 0.635 and 0.681 or 0.734 before and after the transition period, respectively. Through time it shifts up to higher correlation levels during turmoil periods of ISX100. This second transition variable generates very similar conditional correlation dynamics for ISX100 – DAX and ISX100 – CAC pairs. But there is an important difference in the threshold value which differentiates calm and turmoil regimes. The estimated threshold value, 8.58, in DAX case is lower than the one in CAC case which is 9.06 suggesting that DAX is more sensitive to volatility increases in ISX100 compared to CAC.

From the STCC-GARCH model estimates, it is seen that the conditional correlation between ISX100 and CAC has been smoothly increasing from 0.227 to 0.678. Once again these values can be considered as the average values of the conditional correlation implied by DSTCC-GARCH models. This, in turn, implies that the correlation

is capable of going beyond the 0.678 and can reach to higher level of 0.899. As in the DAX case, the opportunities offered by Turkish stock market considerably declines in terms of international portfolio diversification.

4.3.2.2.3 ISX100 – FTSE: For conditional correlation of ISX100 – FTSE pair, only volatility measures of ISX100 are indicated as significant additional transition variable after controlling for time trend. Among three measures, second lag of absolute error of ISX100 delivers the best fit as in the DAX and CAC cases. The conditional correlation implied by this second variable and time variable within the DSTCC specification is illustrated in Figure 4.12.

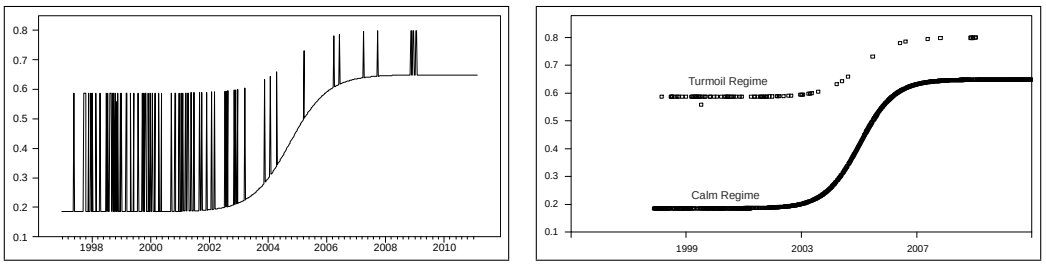


Figure 4.12: The conditional correlation between ISX100 and FTSE from DSTCC-GARCH model with time and second lag of absolute error of ISX100 transition variables.

The speed of transition is relatively slow and from mid-2003 to mid-2007 the transition takes four years to reach to higher correlation levels. When the second transition variable is less (greater) than its threshold value, 9.05, the conditional correlation is said to be in the calm (turmoil) regime. During chaotic times the conditional correlation shifts up from 0.185 to 0.587 and from 0.649 to 0.799 before mid-2003 and after mid-2007 respectively. Thus, similar to ISX100 – DAX and ISX100 – CAC pairs, higher correlation levels are associated with turmoil periods of ISX100 and leave almost no room for international portfolio diversification.

4.3.2.2.4 ISX100 – S&P500: When the time trend is taken in to account, the conditional correlation between ISX100 and S&P500 is not affected by any information from ISX100. The volatility measures of indices in EU countries and the US have explanatory power on dynamic nature of conditional correlation. The time plots of the estimated conditional correlations from DSTCC-GARCH models with time and these additional correlation variables are presented in Figure 4.13. In all models, the transitions with respect to both transition variables take place suddenly. Hence the conditional correlations equal to one of the four regime specific correlations through time and shifts up to higher levels with respect to time variable in October 2003. The responses of conditional correlation to the volatility measures change following the transition to the higher correlation levels. Before this date,

the conditional correlations tend to increase when the volatilities of indices rise, but since then they tends to decrease with the rise in the volatilities of indices. Before October 2003, when the first lag of absolute standardized error of S&P500 and first lag of absolute error of DAX are greater than their specific threshold values (1.489 and 0.71), the conditional correlations is said to be in the turmoil regime and shift up from 0.215 to 0.39 and -0.115 to 0.272 respectively. But after the transition in October 2003, they shift down from 0.584 to 0.212 and 0.677 to 0.514 during turmoil periods of S&P500 and DAX respectively (see graphs on the first and second rows in Figure 4.13).

Similarly, the graphs on the third and fourth rows depicted the response of conditional correlation to the volatility measures of CAC and FTSE, first lag of absolute standardized error of CAC and first lag square standardized error of FTSE. If the former transition variable is above its threshold value, 0.951 then CAC is said to be in turmoil regime and turmoil regime in FTSE is identified when the latter is greater than its threshold, 0.437. Before the transition to the higher levels with respect to time variable, turmoil periods of CAC and FTSE result in an increase in the conditional correlation from 0.184 to 0.275 and from 0.142 to 0.285, respectively. But since then turmoil periods of CAC and FTSE leads to a decrease from0.626 to 0.396 and from 0.624 to 0.443.

According to the best DSTCC-GARCH model, the conditional correlation between ISX100 and S&P500 fluctuates between 0.514 and 0.677 since October 2003. Thus, the finding of STCC-GARCH model, 0.553 corresponds to the average values of these correlation levels. Thus the conditional correlations increases further from 0.553 to 0.677 during the calm times and reduce the gains from international portfolio diversification.

4.3.2.3 Comparison of Models

For all index pairs, additional transition function improves the log-likelihood value as expected. To compare the performance of STCC-GARCH and DSTCC-GARCH models, AIC and SIC information criteria are calculated and reported with ML values in Table 4.8. The highlighted values in AIC and SIC columns represent better specification of conditional correlation. For all index pairs, AIC selects the DSTCC specifications. On the other hand STCC specifications are selected by SIC penalizing the number of parameters more strongly. Nevertheless DSTCC-GARCH models enable us to discover the role of factors such as global volatility, index specific volatility and type of news from indices in the dynamic nature of conditional correlations.

Figure 4.13: The conditional correlation between ISX100 and S&P500 from DSTCC-GARCH model with time and stated transition variables.

Table 4.8: Values of log-likelihood and information criteria

		ISX100			
	Model	Transition Variable(s)	ML Value	AIC	SIC
DAX	STCC	Time	-3934.92	7.960	**8.024**
	DSTCC	Time + serr.Tr-L2	-3927.14	**7.952**	8.036
		Time + A[err.Tr]-L2	-3927.42	7.952	8.036
CAC	STCC	Time	-3872.18	7.833	**7.897**
	DSTCC	Time + err.Tr-L2	-3861.82	7.820	7.904
		Time + A[err.Tr]-L2	-3861.30	**7.819**	7.903
FTSE	STCC	Time	-3700.26	7.486	**7.551**
	DSTCC	Time + A[err.Tr]-L2	-3693.09	**7.480**	7.564
S&P500	STCC	Time	-3740.67	7.568	**7.632**
	DSTCC	Time + A[serr.US]-L1	-3736.75	7.568	7.652
		Time + A[err.Ger]-L1	-3734.74	**7.564**	7.648
		Time + A[serr.Fr]-L1	-3735.61	7.566	7.650
		Time + S[serr.UK]-L1	-3736.46	7.567	7.651

4.4 Conclusion

In this chapter, the dynamic nature of conditional correlations between stock markets in Turkey and four developed countries, the US, UK, France and Germany are examined in order to assess the potential of Turkish stock market in providing diversification benefits to international investors. The conditional correlations between stock market indices are modeled in the context of multivariate GARCH (MGARCH) models with time varying conditional correlations by using smooth transition conditional correlation (STCC-GARCH) and double smooth transition conditional correlation (DSTCC-GARCH) models proposed by Silvennoinen and Teräsvirta (2005 and 2009). The first aim of this Chapter is to test the validity of increasing trend in the conditional correlation of stock markets in Turkey and new member countries of EU (namely Hungary, Czech Republic, Poland, Bulgaria and Romania) with stock markets in core countries and the US, and to investigate the possible effects of the status of being a member on the upward trends. In addition, the issue whether the changes in the conditional correlations are dominated by global factors or EU related developments is also addressed. The second aim is to investigate the role of global volatility, index specific volatility and news from indices, which are found to be important factors for international portfolio diversification, in determining the dynamic structure of conditional correlation between Turkish stock market and stock markets in the US, UK, France, Germany.

The estimation results of STCC-GARCH models with time transition variable indicate that the upward trend is valid for conditional correlations of stock markets in Turkey and new members with the developed stock markets in the US, UK, France and Germany, and it seems that these increasing trends may be independent of being a member and cannot solely be attributed to the developments in EU. Since 2005, the average values of conditional correlations equal to 0.553, 0.656, 0.678 and 0.661 with S&P500, FTSE, CAC and DAX, respectively. Besides, estimation results of DSTCC-GARCH models show that the conditional correlation of Turkish stock market with stock markets in EU are highly affected by volatility of Turkish stock market and tend to increase further and reach to 0.799, 0.734 and 0.8 with DAX, CAC and FTSE, respectively during high volatile times in ISX100. On the other hand, the correlation with the stock market in the US is affected by volatility of stock markets in EU and the US. The response of the correlation to volatilities in these markets changes in October 2003. Before this date the conditional correlation tends to increase in turmoil periods and after this date it tends to decline during the turmoil periods. The conditional correlation with S&P500 reaches to 0.677 during low volatility in DAX.

Therefore, since 2005, the conditional correlations between Turkish stock market and developed stock markets are as high as the correlations among developed stock markets, thus attractiveness of ISX100 diminishes in terms of international portfolio diversification.

CHAPTER 5

THE EFFECTS OF FINANCIALIZATION OF COMMODITY MARKETS ON THE DYNAMIC STRUCTURE OF CORRELATIONS AMONG COMMODITY AND STOCK MARKET INDICES

5.1 Introduction

There has been enormous rise in the volume of commodity investment since 2000. The main reason is the financial investors who are recognized as non-commercial participants by Commodity Futures Trading Commission (CFTC). At the end of 2010, their number was three times higher than the number of traditional investors engaging in commodity markets to hedge against commodity price fluctuations (CFTC, 2011). In order to take the advantage of low correlation between commodity and financial markets, financial investors have intensified investment in commodities and included investable commodity indices in their portfolio with the incentive to reduce the risk burden via portfolio diversification. Thus, as an alternative to financial markets, investable commodity indices such as Standard & Poor's Goldman Sachs Commodity Index (S&P-GSCI) or the Dow Jones American International Group Commodity Index (DJ-AIG) or sub-index of these two indices have emerged as an important class of investment instruments. It is estimated that total investment in

various commodity indices increase from $15 billion in 2003 to $200 billion in 2008 (CFTC, 2008) and to $376 billion at the end of 2010 (Barclays Capital, 2011).

The growing role of financial investors in commodity markets gives rise to the term of "financialization of the commodity markets". With this process, the volatility of commodity markets and the correlation among commodity markets and stock markets are expected to increase since 2000. However, the empirical literature can manage to detect evidence of increasing trend in the correlation after 2010.

This Chapter investigates how the dynamic return correlations of investable agricultural commodity and precious metal sub-indices with stock market index are evolved during the financialization of commodity market. More specifically, the conditional correlations of investable S&P-GSCI Agricultural Commodity and Precious Metal sub-index returns with S&P500 index return are modeled in the context of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) with time varying conditional correlations. Similar to previous Chapters, the first aim is to search for evidence of increasing trend in the conditional correlation which is expected as a natural result of financialization process. The second one is to examine how conditional correlations are affected by global volatility, index specific volatility and the sign of the news from the indices by considering various measures of these factors as candidate transition variable in the context of STCC-GARCH and DSTCC-GARCH models. The results imply that the increasing trend hypothesis is valid for precious metal commodity market but not for agricultural commodity market. For precious metal sub-index, only information about precious metal sub-index have explanatory power over time variable. On the other hand, volatilities of agricultural commodity and stock market indices play key role in determining the correlation between agricultural commodity and stock market indices.

5.2 Literature Survey

The earlier literature employing price data up to 2004 reveal that the correlation between return of commodities and returns of stock and bond markets are very low. Using monthly data from December 1970 to December 1999, Greer (2000) shows that average total return and volatility of Chase Physical Commodity (CPC) index are comparable to those of stock market (S&P500) and bonds (Lehman Long T-bond (LL T-bond)), and reports that CPC index returns are negatively correlated with S&P500 and LL T-bond but positively correlated with inflation. Therefore, he argues that CPC index can be an alternative investment to stock and bond, and offer not only diversification benefits but also hedging opportunities against the inflation. Instead of using investable commodity index, Gorton and Rouwenhorst (2006) construct an equally weighted commodity index for the period between July 1959 and December 2004, and report that the return correlations of the constructed

index with the stocks and bonds are very low and even negative for longer periods. Besides, they indicate that the risk premium of their index is equal to the risk premium of stocks and higher than bonds risk premium. Thus, commodity futures or various investable commodity indices formed by commodity futures with various weights are attractive investment instruments for portfolio diversification. As well as with stocks and bonds, the earlier literature uncovers that the return correlations of commodities with each other are also very low. For instant, Erb and Harvey (2005) investigate the correlation structure among commodity markets with monthly data from December 1982 to May 2004 and conclude that average return correlation of commodities with one another is only 0.09.

The findings of earlier literature imply that investment in commodity markets can provide significant reduction in the risk of a portfolio consisting of stocks and bonds. This suggestion is tested by various studies. Becker and Finnerty (1994) add S&P-GSCI commodity index to hypothetical portfolio containing stocks and bonds, and find that inclusion of commodity index improves the return and risk performance for the period between 1970 and 1990. They underline that the gain is more apparent in high inflationary years of 1970s than 1980s and argue that commodity indices can also provide hedge against inflation. Similarly, Georgiev (2001) constructs several hypothetical portfolios formed by stocks, bonds, commodity index and hedge fund index with various weights. From monthly data from January 1990 to December 2001, Georgiev reports that as a single investment instrument S&P-GSCI index underperforms S&P500 but it can produce investment benefits when considered as an addition to diversified portfolio with its low and negative correlation with stocks, bonds and hedge fund indices. The annualized standard deviation of a hypothetical portfolio of stocks and bonds reduces from 8.1% to 6.9% when commodity and hedge fund indices are added, and risk adjusted performance measured by the Sharpe ratio of the portfolio increases from 0.65 to 0.74. For longer period from January 1976 to April 2004, Hillier et al. (2006) consider the precious metals, namely gold, platinum and silver with daily data and evaluate the benefits of diversifying strategies to cover these commodities. They conclude that portfolios including precious metals perform significantly better than S&P500 and illustrate that a portfolio containing 30% gold generates 34% efficiency gain measured as a ratio of standardized return. Similarly, 15% silver and 20% platinum generate 18% and 24% efficiency gains, respectively. Besides, their results imply that during high stock market volatility, returns of precious metals are more negatively correlated with stock market returns suggesting higher diversification benefits in volatile times of S&P500.

Since 2004, the increasing role of financial investors in the commodity markets, which give rise to the term of "financialization of the commodity markets", creates the expectation of upward trend in the correlation of commodity markets with stock markets, as well as with each other. However, increasing trend in return corre-

lation between commodity and stock markets cannot be identified until mid-2009. For example, Büyükşahin et al. (2008) cannot find evidence of increasing trend in the correlation between investable commodity indices (S&P-GSCI and DJ-AIG, and their sub-indices) and stock market index, S&P500, using dynamic correlation and recursive co-integration models for the period from January 1991 to May 2008. They report that there is no evidence of increase in correlation even during periods of extreme returns. On the other hand, Silvennoinen and Thorp (2010) manage to find evidence of increasing trend in the correlations between commodity and stock market indices. They investigate the dynamic nature of the correlations among commodity indices and stock markets in the US, UK, Germany and France under the DSTCC-GARCH framework with weekly data covering the period from May 1990 to July 2009. Silvennoinen and Thorp (2010) show that the correlations of agricultural commodities and precious metals except gold start to increase between the years 2004 and 2007, and reach to 0.5 levels. Similarly, Tang and Xiong (2010) document that the return correlation between S&P-GSCI and S&P500 significantly increases in September 2008 which coincides with the initiation of financial crisis in the US. Besides, this analysis highlights that the return correlations among commodities start to increase after 2004, i.e. long before the increase in correlations between commodity and stock markets. Büyükşahin et al. (2011) find similar results for energy sub-indices of S&P-GSCI by modeling correlations between weekly returns during the period from January 1991 to May 2011 in the DCC-GARCH framework. The results indicate that the correlation between S&P-GSCI energy index and S&P500 is time varying without a particular trend until September 2008, but since then the correlation exhibits an upward trend and reaches to very high levels unseen in the prior two decades.

In a different study, Geetesh and Dunsby (2012) investigate whether the documented recent increase in correlation structure can be considered as permanent. They report that tests for a structural break cannot detect an evidence of permanent increase. The analysis of Geetesh and Dunsby (2012) reveals that the correlation between commodity and stock markets is higher during economic weakness and they attribute the recent increase to the slowdowns in the GDP growth rates.

It should be noted that, except Silvennoinen and Thorp (2010), all these studies employ models which are not as flexible as STCC and DSTCC specifications as pointed out in Chapter 2. This Chapter therefore analyze the nature of correlations between commodity and stock markets with these models.

5.3 Data and Empirical Results

5.3.1 Data

Weekly return rates of S&P-GSCI Agriculture (S&P-AG) and Precious Metal (S&P-PM) sub-indices, and S&P500 index denominated in US dollar for the period from January 4, 1990 to December 30, 2010 are used in the estimations. The weekly return rates are calculated by log-differencing[1] Thursday closing prices[2]. The data is obtained from Global Financial Data. The extreme returns which are outside the four standard deviations confidence interval around the mean are replaced with their boundary values. This truncation is necessary not only in estimation of GARCH parameters but also to alleviate the effects of outliers on LM tests used in determining appropriate transition variables. Figure 5.1 represents the normalized price series of indices. The price of January 04, 1990 and June 20, 2002 are normalized to 1 in the upper and lower graphs, respectively.

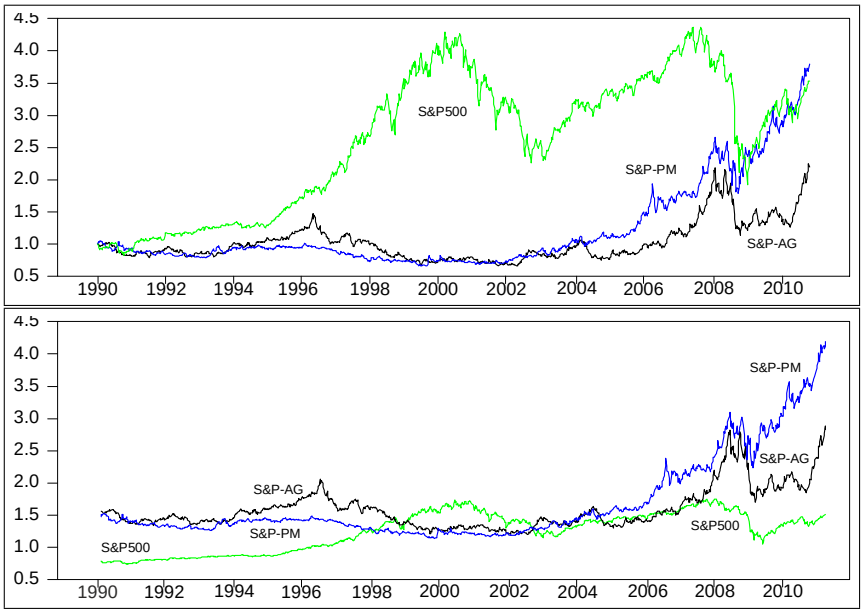


Figure 5.1: Weekly price series of S&P-GSCI Agricultural, S&P-GSCI Precious Metal and S&P500 Indices

The better performance of stock market towards the mid-2002 is apparent from the upper graph in Figure 5.1. However as indicated by lower graph, commodity sub-indices, especially S&P-PM, outperform the stock market indices since 2003. For the

[1] $R_{it} = (\log(P_{it}) - \log(P_{it-1})) \times 100$, where P_{it} is the Thursday closing price of stock market i at time t.

[2] The choice of Thursday closing price reflects the attemp to avoid possible end-of-week effects on closing prices.

whole sample period, S&P-PM posses the highest mean return rate and it is followed by S&P500 (see Table 5.1). Interestingly, contrary to risk-return trade-off, there is negative relationship between risk and return for the period under investigation; the highest volatility level corresponds to the lowest mean return (S&P-AG) and the lowest volatility corresponds to the highest mean return level (S&P-PM). The S&P-AG and S&P500 indices are left skewed a typical feature common to most of the financial time series. Besides, the fat tail property of financial time series is also apparent from the excess kurtosis of all indices, hence observing extreme returns are more likely. But the S&P-PM index is right skewed implying that large negative returns are not as likely as large positive returns which means that precious metal index is not more risky in terms of losses either.

Table 5.1: Descriptive Statistics of Weekly Returns

	Mean	Standard Deviation	Skewness	Kurtosis (excess)
S&P-AG	0.072	2.53	-0.372	3.98
S&P-PM	0.122	2.289	0.207	6.11
S&P500	0.116	2.383	-1.094	11.55

The unconditional sample correlation among indices are presented in Table 5.2. The correlation levels are very low relative to the correlation among international stock market indices and it is almost zero between precious metal and stock market indices supporting the view that agricultural and precious metal commodity indices may offer valuable opportunities to reduce risk via portfolio diversification.

Table 5.2: Sample Correlations of Weekly Returns

	S&P-AG	S&P-PM	S&P500
S&P-AG	1	0.275	0.138
S&P-PM		1	0.011

5.3.2 Empirical Results

5.3.2.1 STCC-GARCH Model

In line with the modeling procedure, the significant transition variables for conditional correlation equation are determined by LM_1 test of Silvennoinen and Teräsvirta (2005). Testing increasing trend hypothesis postulates time as the appropriate transition variable, but all variables in the other three groups, global volatility, index specific volatility and the news from the indices introduced in Section 2.4.1, are also

considered with their four lags as candidate transition variables. Therefore VIX, lagged conditional variance, lagged absolute error and lagged absolute standardized error, lagged squared error and lagged squared standardized errors, lagged errors and lagged standardized error are used in LM_1 test making 61 candidate variables including lagged variables. This strategy enables not only to find out the effects of these variables on the dynamic structure of conditional correlation but also to be sure that time is the optimal transition variable in conditional correlation equation. Silvennoinen and Thorp (2010) also use STCC specification for conditional correlation. They confine correlation analysis by considering four transition variables; time, the lagged level of the VIX index, the lagged percentage of long open interest held by non-commercial traders, and the lagged percentage difference between long and short open interest by non-commercial traders divided by total percentage non-commercial interest but do not consider the possible effects of volatility measures of commodity and stock markets indices.

The significant transition variables for conditional correlations of S&P-AG and S&P-PM with S&P500 are reported in Table 5.3. As seen, the CCC hypothesis is rejected at 1% significance level for both commodity sub-indices if time is used. Therefore, at this stage it can be concluded that there is a time trend in the conditional correlations of both S&P-AG and S&P-PM and their structures can be revealed after the estimation of STCC-GARCH model with time transition variable. In addition to time variable, the significant transition variables for conditional correlation of S&P500 with

- S&P-AG are global volatility represented by second lag of VIX and two volatility measures of S&P500 and S&P-AG, second lag of conditional volatility of S&P500, fourth lag of squared error of S&P500, fourth lag of conditional volatility of S&P-AG and second lag of squared standardized error of S&P-AG.
- S&P-PM are news from both S&P500 and S&P-PM represented by error and standardized error, and two volatility measures of both S&P500 and S&P-PM

It should be mentioned that the most significant candidate transition variable in modeling conditional correlation between S&P-AG and S&P500 index within STCC specification is the fourth lag of conditional volatility of S&P-AG which is not covered in a similar study of Silvennoinen and Thorp (2010).

Since the p-values reported in Table 5.3 are very close to each other, STCC-GARCH models are estimated with all significant transition variables and the selection of best transition variable is postponed to post-estimation. The results show that for both index pairs time variable provides the best fit according to ML values. Table **??**

Table 5.3: The LM statistics of testing constant conditional correlation against STCC-GARCH model with various transition variables.

S&P-AG – S&P500			S&P-PM – S&P500		
Transition variable	LM-stat.	p-value	Transition variable	LM-stat.	p-value
Time	8.06^a	0.004	Time	14.77^a	0.000
VIX-L2	10.03^a	0.001	err.PM-L2	7.56^a	0.006
vol.SP-L2	8.72^a	0.003	serr.PM-L2	6.78^a	0.009
S[err.SP]-L4	5.34^b	0.021	err.SP-L1	5.69^b	0.017
vol.AG-L4	14.53^a	0.000	serr.SP-L1	5.55^b	0.018
S[serr.AG]-L2	4.08^b	0.043	A[err.PM]-L2	8.25^a	0.004
			S[err.PM]-L2	7.26^a	0.007
			A[serr.SP]-L1	4.13^b	0.042
			S[serr.SP]-L1	6.54^b	0.010

Notes: This table represents the LM statistic to test constant conditional correlation null hypothesis with respect to particular transition variable.The LM statistics is evaluated with the estimated parameters from the restricted model of CCC reported in Appendix A.3 (see Silvennoinen and Teräsvirta, 2005). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively."-Li" is the ith lag of the particular variable."SP", "AG" and "PM" represent S&P500, S&P-AG and S&P-PM indices. (a), (b) and (c) denote significance at 1%, 5% and 10% levels respectively.

reports the estimates of parameters in conditional correlation equations for both pairs[3].

The implied conditional correlation of S&P-AG and S&P-PM with S&P500 by the best STCC-GARCH models are plotted in Figures 5.2 and 5.3, respectively. Both figures visualize an upward trend in the conditional correlation. The conditional correlation between S&P-AG and S&P500 is very close to zero until September 2008 and shifts up to 0.458 in this date. This result is in accordance with the finding of Tang and Xiong (2010) and Büyükşahin et al. (2011) that the correlation between commodity and stock markets starts to increase during the recent financial crisis in the US and EU but contradicts with the results of Silvennoinen and Thorp (2010) who report that increasing trend started in as early as mid-2000s.

On the other hand, the conditional correlation of S&P-PM with S&P500 is -0.1 until November 2003 and shifts up to 0.161 in this date which agrees with Silvennoinen and Thorp (2010) but contradicts with Tang and Xiong (2010) and Büyükşahin et al. (2011). The indication of more than one significant transition variables in both index pairs suggest that the STCC specification may not be adequate and additional transition variable is needed. Thus, the STCC-GARCH models may subject to cor-

[3]The estimation results of mean and variance equations are reported in Appendix B.3.

Table 5.4: The estimation results of STCC-GARCH model with time transition variables.

		S&P-AG – S&P500				
Transition Variable	ML-value	P_1	P_2	γ	c	H_0:P_1=P_2
Time	-4708.325	0.007	0.458^a	400	0.89^a	28.57^a
		(0.034)	(0.075)	-	(0.004)	[0.000]
		S&P-PM – S&P500				
Transition Variable	ML-value	P_1	P_2	γ	c	H_0:P_1=P_2
Time	-4527.69	-0.10^a	0.161^a	400	0.662^a	20.09^a
		(0.036)	(0.046)	-	(0.005)	[0.000]

Notes: This table reports the estimation results of parameters in conditional correlation and transition function which is described by equations 4.3 from the STCC-GARCH model with time transition variable. The mean and variance equations are given by 4.1 and 4.2, respectively. The last column reports the Wald statistics of testing the stated null hypothesis. Values in parenthesis and square brackets are standard errors and p-values, respectively. 400 is the upper constraint for speed parameters. (a) denotes significance at 1% level.

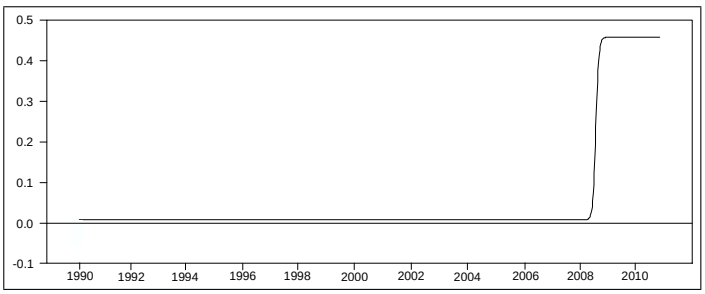


Figure 5.2: The conditional correlation between S&P-AG and S&P500 from STCC-GARCH model with time transition variable

rection and the results should be interpreted cautiously until the estimation results and the optimality of time variable are justified by DSTCC-GARCH estimates.

In order to determine whether each significant transition variable carry specific and unique information on the dynamic structure of conditional correlation, all estimated STCC-GARCH models are tested for additional transition variable with LM_2 test of Silvennoinen and Teräsvirta (2009) by considering same 61 candidate variables as additional transition variable. If one variable has specific and unique information which cannot be captured by other variables, then it is expected that this variable appears as a significant additional variable in estimated STCC-GARCH model with other transition variables. For S&P-PM sub-index, time variable is indicated as an additional transition variable in all STCC-GARCH models with transition variables other than time suggesting time variable should be one of the transition variable. The significant additional transition variables to the estimated STCC-GARCH model with time variable are reported in Table 5.5. As expected, LM_2 test rejects the null hypothesis of STCC-GARCH model with time in favor of DSTCC-GARCH model

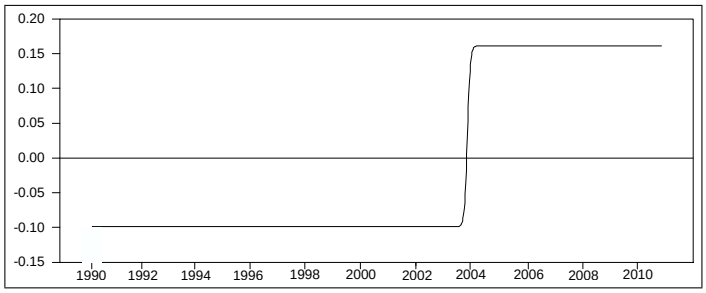


Figure 5.3: The conditional correlation between S&P-PM and S&P500 from STCC-GARCH model with time transition variable

with time and additional transition variables which are also indicated as alternative transition variables to time by LM_1 test. Since p-values are very close, all DSTCC-GARCH models for all significant additional transition variables are estimated.

For S&P-AG sub-index, as discussed before, LM_1 test rejects the null of CCC hypothesis against STCC-GARCH model most significantly when fourth lag of conditional volatility of S&P-AG is used, time comes the second variable but the STCC specification with time variable delivers better fit than the STCC-GARCH model with fourth lag of conditional volatility of S&P-AG. However, LM_2 test cannot reject the STCC-GARCH model with fourth lag of conditional volatility of S&P-AG against DSTCC-GARCH model with time and this variable. Besides, when LM test is applied under the null hypothesis of STCC-GARCH with time variaable, it rejects the null hypothesis in favor of only DSTCC-GARCH with time and second lag of square of standardized error of S&P-AG. Hence it is difficult to conclude that time should be one of the transition variable at this point and the significant additional transition variables for all estimated STCC-GARCH models are reported in Table 5.5. DSTCC-GARCH models are estimated with the following pairs of transition pariables; time and second lag of conditional volatility of S&P500, time and second lag of VIX, fourth lag of conditional volatility of S&P-AG and second lag of conditional volatility of S&P500, and fourth lag of conditional volatility of S&P-AG and second lag of VIX.

5.3.2.2 DSTCC-GARCH Model

After eliminating the unsuccessful models, the estimation results of the best DSTCC-GARCH models corresponding to each variable groups are reported in Table 5.6.

5.3.2.2.1 S&P-AG – S&P500: The estimated conditional correlations between S&P-AG and S&P500 from two successful DSTCC-GARCH models using time and second lag of conditional volatility of S&P500, and time and second lag of VIX are depicted in Figure 5.4.

Table 5.5: The LM statistics of testing estimated STCC-GARCH model for an additional transition variable.

S&P-AG – S&P500				S&P-PM – S&P500			
1^{st} Transition Var.	Add. Transition Var.	LM-stat	p-value	1^{st} Transition Var.	Add. Transition Var.	LM-stat	p-value
Time	S[serr.AG]-L2	3.93^{b}	0.047	Time	err.PM-L2	4.61^{b}	0.032
vol.AG-L4	vol.SP-L2	6.83^{a}	0.009		serr.PM-L2	4.34^{b}	0.037
	VIX-L2	5.80^{b}	0.016		err.SP-L1	6.38^{b}	0.011
	S[err.SP]-L4	4.44^{b}	0.035		serr.SP-L1	5.89^{b}	0.015
	S[serr.AG]-L2	4.06^{b}	0.044		A[err.PM]-L4	5.47^{b}	0.019
vol.SP-L2	vol.AG-L2	8.32^{a}	0.004		S[err.PM]-L4	11.11^{a}	0.000
	S[serr.AG]-L2	5.74^{b}	0.016		S[serr.SP]-L1	5.75^{b}	0.016
	Time	4.95^{b}	0.026				
VIX-L2	vol.AG-L2	6.31^{b}	0.012				
	Time	5.24^{b}	0.022				
	S[serr.AG]-L2	4.73^{b}	0.029				

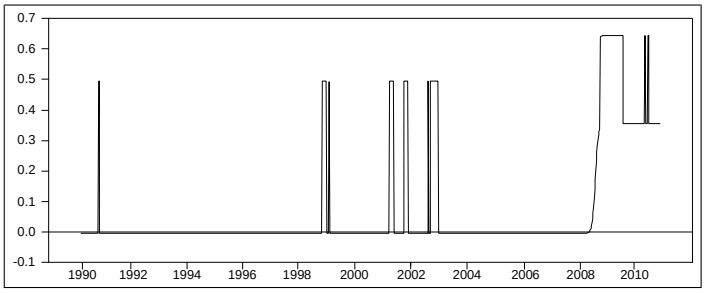
Notes: This table represents the LM statistics of testing estimated STCC-GARCH model with stated first transition variable for additional transition variables. The LM statistics is evaluated with the estimated parameters from the restricted model of STCC-GARCH model (see Silvennoinen and Teräsvirta, 2009). "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively."-Li" is the ith lag of the particular variable."AG", "PM" and "SP" represent S&P-AG, S&P-PM and S&P500. (a) and (b) denote significance at 1% and 5% levels, respectively.

Table 5.6: The estimation results of DSTCC-GARCH models with the stated transition variables

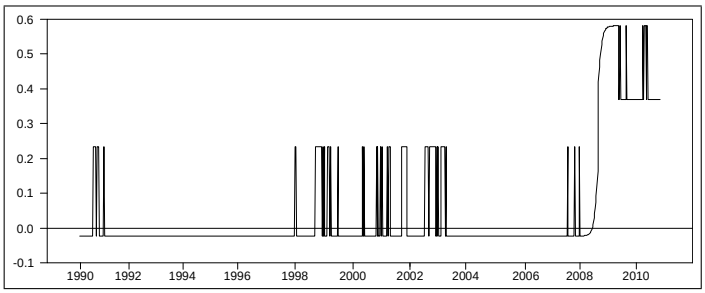
S&P-AG – S&P500											
Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
Time + vol.SP-L2	-4702.67	-0.003	0.485^a	0.357^a	0.646^a	400	400	0.889^a	9.99^a	21.30^a	5.17^b
		(0.027)	(0.117)	(0.093)	(0.086)	-	-	(0.008)	(1.546)	[0.000]	[0.023]
Time + VIX-L2	-4703.99	-0.022	0.235^b	0.369^a	0.580^a	277	400	0.894^a	27.98^a	6.55^b	1.93
		(0.033)	(0.094)	(0.116)	(0.104)	241	-	(0.007)	(0.669)	[0.010]	[0.164]
vol.AG-L4 + vol.SP-L2	-4700.22	-0.052^a	0.053	0.139^a	0.621^a	400	400	5.59^a	7.72^a	0.88	44.23^a
		(0.007)	(0.104)	(0.046)	(0.054)	-	-	(0.096)	(0.68)	[0.348]	[0.000]
vol.AG-L4 + VIX-L2	-4702.08	-0.043	0.079	0.105^b	0.573^a	400	400	5.87^a	27.98	1.20	31.49^a
		(0.039)	(0.105)	(0.053)	(0.064)	-	-	(0.344)	(600)	[0.273]	[0.000]
S&P-PM – S&P500											
Transition Variables	ML-value	P_{11}	P_{12}	P_{21}	P_{22}	γ_1	γ_2	c_1	c_2	H_0:P_{11}=P_{12}	H_0:P_{21}=P_{22}
Time + err.PM-L2	-4521.84	-0.089^a	0.116^c	0.155	0.585^a	400	400	0.897^a	1.507^a	7.42^a	137.1^a
		(0.035)	(0.066)	(0.107)	(0.076)	-	-	(0.005)	(0.011)	[0.006]	[0.000]
Time + S[err.PM]-L4	-4522.22	-0.125^a	0.035	0.725^a	0.228^a	400	396	0.896^a	1.349^a	5.59^b	113.2^a
		(0.039)	(0.046)	(0.046)	(0.002)	-	(100)	(0.005)	(0.010)	[0.018]	[0.000]

Notes: This table reports the estimation results of parameters in conditional correlation equation 4.4 from DSTCC-GARCH model with the stated transition variables. The mean and variance equations are given by 4.1 and 4.2 respectively. Values in parenthesis are standard errors. 400 is the upper constraint for speed parameters. (a), (b) and (c) denote significance at 1%, 5% and 10% levels, respectively. "err" and "serr" are error and standardized error from GARCH (1,1) process. S[.] and A[.] represent square and absolute value of square brackets respectively."-Li" is the i-th lag of the particular variable."AG", "PM" and "SP" represent S&P-AG, S&P-PM and S&P500 indices.

As a second transition variable, these measures of global volatility and volatility of S&P500 imply very similar dynamics for the conditional correlation between agricultural commodity sub-index and stock market index. In both models, there are no transition periods with respect to first transition variable, time, and conditional correlation shifts up to higher levels in August 2008 and in October 2008 in models using second lag of conditional volatility of S&P500 and second lag of VIX as second transition variables. According to both volatility measures, through time, the conditional correlations increase to higher correlation levels during the high volatile times.



vol.S&P500-L2



VIX-L2

Figure 5.4: The conditional correlation between S&P-AG and S&P500 from the DSTCC-GARCH model with time and stated second transition variable

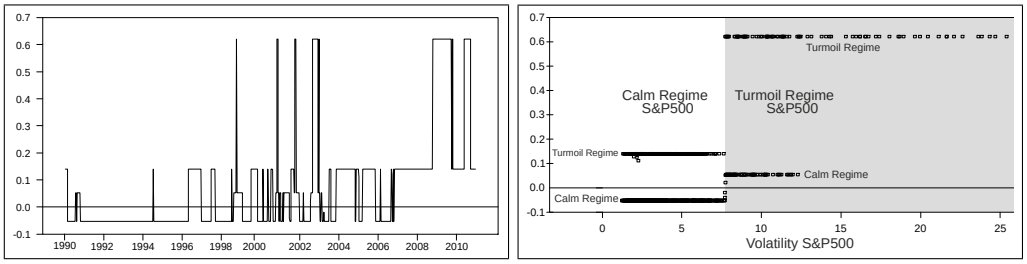
Similarly, Silvennoinen and Thorp (2010) employ VIX index to investigate the effects of global volatility and find that global turmoils lead to shift up in the conditional correlation levels but they do not consider conditional volatility of S&P500 index. However, although they may be containing similar information, as Table 5.6 indicates using volatility measure of S&P500 instead of VIX produce better fit according to loglikelihood values. Thus, the correlation levels implied by the model with time and second lag of conditional volatility of S&P500 are interpreted below.

When second transition variable, second lag of conditional volatility of S&P500, is below its threshold value of 9.99, the conditional correlation is said to be in the calm regime. Before transition to the higher correlation levels in August 2008, there is

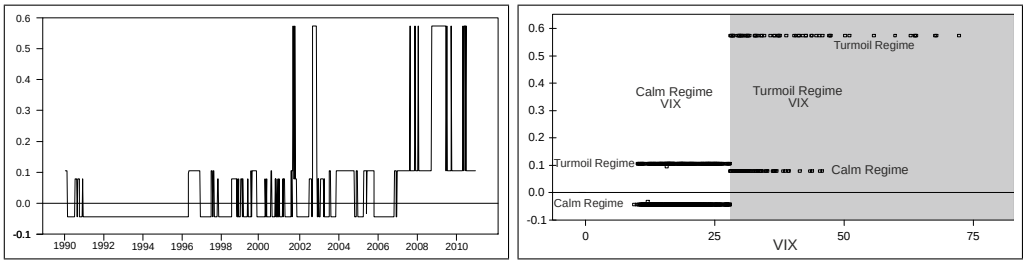
no significant correlation during calm periods but when the volatility increases the conditional correlation shifts to 0.485. However since the last quarter of 2008 the conditional correlation fluctuates between 0.357 and 0.646 according to the state of the stock market; during calm periods it is 0.357 but during turbulence times it increases to higher level, 0.646 (see upper graphs in Figure 5.4). Thus higher correlation levels (0.485 and 0.646) are associated with turmoil regime in both periods. When the volatility is low (it is less than 9.99) the conditional correlation takes on either -0.003 or 0.357 through time and when it is high it is either 0.485 or 0.646.

Before the recent financial crisis, the conditional correlation between agricultural commodity sub-index and stock market index increases to very high level, 0.485, during the volatile years 1991, 1999, 2001, 2002 and 2003. But the correlation level attained during the recent turbulence period (0.646) is higher than those attained during earlier volatile periods. Besides, the conditional correlations of calm periods in the aftermath of the recent financial crisis are also higher than those corresponding to calm periods of pre-crisis. Thus, it can be concluded that there is an increasing trend in the conditional correlation during both low and high volatile periods. However a better representation of conditional correlation dynamics is generated by the DSTCC-GARCH model using fourth lag of conditional volatility of S&P-AG as a first transition variable instead of time variable. Similarly, with this first transition variable second lag of conditional volatility of S&P500 and second lag of VIX are indicated as additional transition variables. Although they produce very similar patterns, the volatility measures of S&P500 index is preferred as a second transition variable according to ML values. The estimated conditional correlation from DSTCC-GARCH model which employs fourth lag of conditional volatility of S&P-AG and second lag of conditional volatility of S&P500 as transition variables are shown in Figure 5.5.

The upper graphs in Figure 5.5 implies that the recent surge of volatility has not specific effects on the conditional correlation which are distinct from the previous volatile years 1999, 2001, 2002 and 2003. Thus the levels as high as 0.621 are not new phenomenon and cannot be attributed to the recent financial crisis. Instead, the conditional correlation between S&P-AG and S&P500 sometimes shifts to the such high levels above 0.6 since 1999. When the second transition variable, volatility measure of S&P500 is less than its threshold value, 7.72, the conditional correlation is said to in the calm regime with respect to S&P500 represented by white region in the upper right graph in Figure 5.5. In this regime, the conditional correlation fluctuates between -0.052 and 0.139 according to the state of agricultural commodity sub-index: If the volatility in the S&P-AG is also low (i.e. volatility measure of S&P-AG is lower than its threshold value of 5.59) then the conditional correlation is equal to -0.052. On the other hand if the volatility of S&P-AG increases but volatility of S&P500 is still low then the conditional correlation is 0.139. However if the volatility in the



vol.S&P500-L2 vol.S&P500-L2



VIX-L2 VIX-L2

Figure 5.5: The conditional correlation between S&P-AG and S&P500 from the DSTCC-GARCH model with fourth lag of conditional volatility of S&P-AG and stated second transition variable

S&P500 increases, represented by the grey region, the conditional correlation starts to fluctuates between 0.053 and 0.621. Thus the conditional correlation reaches to the highest level, 0.621, during volatile periods of both indices.

It should be noted that the effect of an increase in volatility of stock market on conditional correlation is modest (leads to increase from -0.052 to 0.053) if the commodity market is in calm periods but its effect is very strong (leads to increase from 0.139 to 0.621) if the commodity market is in turbulence period.

The increase in average value of conditional correlation through time (since 2007) is also captured from this estimation results but it is not enough to conclude that there is an increasing trend in the conditional correlation and it seems that the abroupt shift up to higher correlation levels in 2007 is not permanent. The lower bound of correlation (0.139) is determined by the condition of agricultural commodity market and if the volatility of S&P-AG declines then the conditional correlation decreases from 0.139 to 0.053. Thus the high values of correlation during the recent crisis can be attributed to the high volatility phase of both indices and it seems that the conditional correlation between indices may return back to low values if the volatility levels in both markets decline. This conclusion supports the findings of Geetesh and Dunsby (2012) stating that recent documented increase in correlations among commodity and stock markets cannot be considered as permanent. On the

other hand, our results reveal that the volatility measures of indices play key role in explaining the correlation structure of agricultural commodity sub-index and their effects have to be considered. Thus the findings of Silvennoinen and Thorp (2010) who do not take volatilities of indices in to account may not represent the accurate correlation dynamics of agricultural commodities with stock market indices.

5.3.2.2.2 S&P-PM – S&P500: As Table 5.5 clearly indicates, news from both S&P-PM and S&P500 and volatility measures of S&P-PM and S&P500 carry significant information after controlling for time trend. However information from S&P500 index (both type of the news and volatility) cannot generate successful DSTCC-GARCH models. Thus the estimation results of two DSTCC-GARCH models using time and second lag of error of S&P-PM, and time and fourth lag squared error of S&P-PM as a second transition variable are reported. The implied conditional correlations are depicted in Figure 5.6.

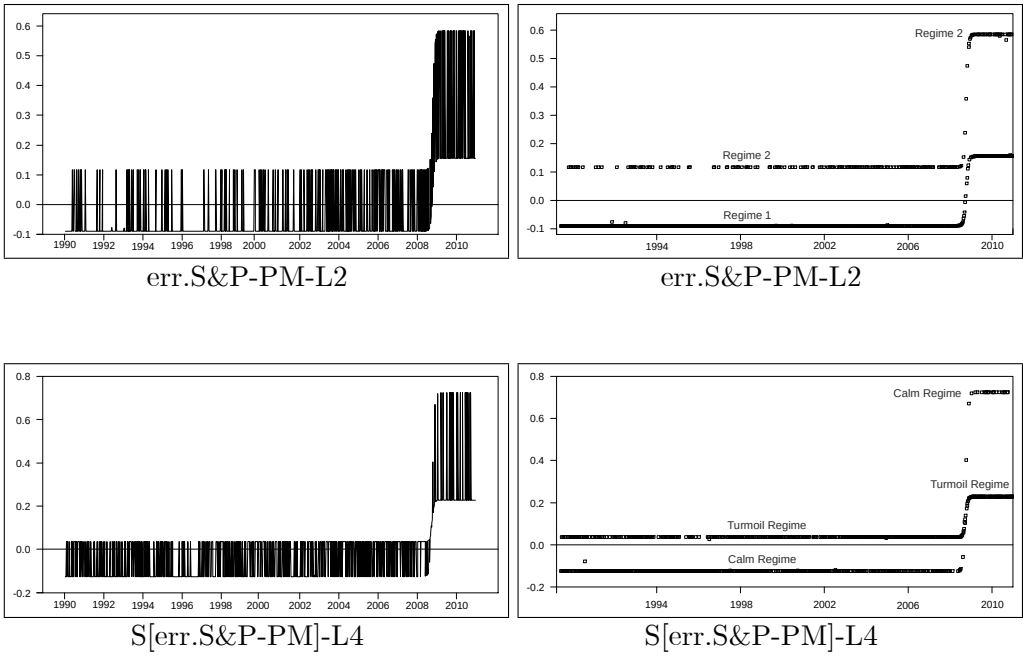


Figure 5.6: The conditional correlation between S&P-PM and S&P500 from the DSTCC-GARCH model with time and stated second transition variable

The upper graphs correspond to the transition variables of time and second lag of error of precious metal sub-index. The conditional correlation moves to higher correlation levels abruptly in October 2008. According to the value of second transition variable, the conditional correlation is either -0.089 or 0.116 and 0.155 or 0.585 before and after this date, respectively. Due to non-zero threshold value of second transition variable, it is not possible to distinguish specific regimes as good and bad.

Thus it is preferred to call first (second) regime if it is below (above) the threshold value, 1.507. If the error is greater than 1.507, the conditional correlation increases from -0.089 to 0.116 and from 0.155 to 0.585 before and after the transition to the higher correlation levels, respectively.

The lower graphs in Figure 5.6 show the implied conditional correlation by next successful DSTCC-GARCH model with time and fourth lag of squared error of S&P-PM. Similar to previous case, the conditional correlation shifts up to higher correlation levels in October 2008. Before this date, it fluctuates between -0.125 and 0.035 but since then it is either 0.725 or 0.228 according to the volatility of S&P-PM sub-index. Through time, higher or lower correlation levels are not associated with one regime with respect to volatility of S&P-PM and the response of conditional correlation to the volatility of S&P-PM changes in October 2008. Before October 2008, it increases from -0.125 to 0.035 during turmoil periods but after this date it decreases from 0.725 to 0.228 during turmoil periods (see lower right graph in Figure 5.6).

Therefore the estimation results support Silvennoinen and Thorp (2010) that there is an increasing trend in the conditional correlation between S&P-PM and S&P500. However, the timing of upward trend agree with Tang and Xiong (2010) and Büyükşahin et al. (2011) that the increasing trend coincide with the recent financial crisis.

5.3.2.3 Comparison of Models

Table 5.7 reports the AIC and SIC information criteria with ML values to compare the performance of STCC-GARCH and DSTCC-GARCH models. The highlighted values in AIC and SIC columns represent better specification of conditional correlation. For both index pairs, AIC selects the DSTCC specification while STCC specifications are selected by SIC penalizing the number of parameters more strongly. Although DSTCC-GARCH models are not preferred by SIC, these models enable us to discover the role of factors such as global volatility, index specific volatility and type of news from indices in the dynamic nature of conditional correlations.

5.4 Conclusion

This Chapter investigates how the dynamic structures of correlations between agricultural commodity sub-index and stock market index, and precious metal sub-index and stock market index are evolved during the so-called financialization of commodity markets. The dynamic conditional correlations between indices are modeled with

Table 5.7: Values of log-likelihood and information criteria

		S&P500			
	Model	Transition Variable(s)	ML Value	AIC	SIC
S&P-AG	STCC	Time	-4708.32	9.517	**9.576**
	DSTCC	Time + vol.SP-L2	-4702.67	9.513	9.592
		Time + VIX-L2	-4703.99	9.516	9.595
		vol.AG-L4 + vol.SP-L2	-4700.22	**9.509**	9.588
		vol.AG-L4 + VIX-L2	-4702.08	9.512	9.591
S&P-PM	STCC	Time	-4527.69	9.153	**9.212**
	DSTCC	Time + err.PM-L2	-4521.84	**9.149**	9.228
		Time + S[err.PM]-L4	-4522.22	9.150	9.229

time varying conditional correlations in the context of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) models. By using the flexibility of STCC-GARCH and DSTCC-GARCH models, this chapter searches for evidence of increasing trend in the correlation by using time as a transition variable in the conditional correlation equation and analyzes the factors which are capable of explaining the properties and structure of correlation.

As far as the conditional correlation of agricultural commodity sub-index is concerned, the evidences are not enough to conclude that there is an upward trend. Instead, the estimation results uncover that the increase in correlation between agricultural commodity and stock market indices are not a new phenomenon and cannot be attributed to the recent financial crisis. Since 1999, it shifts to the higher levels, above 0.6, if both S&P-AG and S&P500 are in volatile phase. However the average value of correlation between indices has been increasing since 2007, but it is not enough to conclude that there is an increasing trend in the correlation during the period of financialization of agricultural commodity markets. It is also found that measures of global and index specific volatilities determine the dynamic structure of correlation and during turbulence periods the correlation shifts to the higher levels. It seems that current high levels of correlation due to high value of index specific volatilities, especially due to stock market volatility and the correlation may return back to its low levels if the markets become calm.

On the other hand, evidence of increasing trend in the conditional correlation of precious metal sub-index is uncovered. The conditional correlation shifts to the higher correlation levels in October 2008. Before this date, although it is on average zero, it can be as low as -0.125 and as high as 0.116 according to the news from S&P-PM and volatility of S&P-PM. Since the last quarter of 2008, the conditional correlation has reached to 0.725 which is as high as the correlation between developed stock market indices implying significant decline in portfolio diversification benefits.

CONCLUSIONS

In the recent literature, there has been a growing interest in modeling correlations to investigate the properties and the structure of dependence among financial assets and markets in both national and international levels. It is now well established that the correlations among financial markets of developed countries are very high due to factors such as developments in information technology, establishment of multinational companies, and liberalization of financial systems and capital markets which leave little room for portfolio diversification. Hence, it is worth to examine the correlation dynamics of alternative markets with developed stock markets. To this end, this thesis considers two emerging countries' stock markets and two commodity markets as alternative markets. More specifically, the conditional correlations of stock markets in Turkey and China, and S&P-GSCI agricultural commodity and precious metal sub-indices with major stock markets are modelled, and their structures and properties are studied to address the issue of whether these alternative markets can provide portfolio diversification benefits.

To incorporate dynamic nature of correlations among international stock markets, we opt for multivariate GARCH (MGARCH) models with time varying conditional correlations. In the literature there are various MGARCH models are proposed but the first model analyzing co-movement by modeling correlation directly instead of straightforward modeling of the conditional covariance in the multivariate GARCH framework is the Constant Conditional Correlation (CCC) model of Bollerslev (1990). In this model variances and covariances are time-varying but correlation is constant over time. However as reported by Tse (2000) and Bera and Kim (2002) constant conditional correlation is not a valid assumption for financial assets, which means that conditional correlation have a dynamic structure. Engle (2002) proposes a new model, Dynamic Conditional Correlation (DCC) which incorporates dynamic structure of conditional correlation by imposing GARCH type dynamics on the conditional correlation. This model employs two-step estimation: the first is separate estimation of univariate GARCH and the second is the correlation estimate using the standardized errors from the first step. Therefore there is no interaction between individual GARCH processes and correlation process. DCC type models employ only lagged values of standardized error in the correlation equation with-

out any search for appropriate explanatory variables for correlation equation. To establish the link between processes in two-step estimation and to offer flexibility in determining the relevant explanatory variable in the conditional correlation new models, Smooth Transition Conditional Correlation (STCC) and Double Smooth Transition Conditional Correlation (DSTCC) to investigate co-movements are proposed by Silvennoinen and Teräsvirta (2005 and 2009). Two extreme regime specific correlations are defined and conditional correlations change smoothly from one regime to another as a function of an observable transition variable. Through time conditional correlation takes values between these two extreme regimes. Chapter 2 provides the advantages and disadvantages of these direct modeling of conditional correlation equation (CCC, DCC, STCC and DSTCC specifications) as well as the indirect modeling (VEC and BEKK specifications) in detail. In this thesis, among the main parametrizations of conditional correlation within the MGARCH framework, smooth transition conditional correlation (STCC-GARCH) and the double smooth transition conditional correlation (DSTCC-GARCH) models are preferred because of their three crucial advantages which can be summarized as the heterogeneity implied by the smooth transition function, the flexibility in choosing the explanatory variables of the conditional correlation equation and more realistic and efficient estimates through simultaneous estimation.

Using the flexibility of STCC and DSTCC specifications, this thesis performs the most comprehensive and up to date return correlation analysis of stock markets in China and Turkey, and two commodity markets (agricultural commodity and precious metal) in three independent and complete chapters. These analyses are undertaken for the first time for Chinese and Turkish stock markets and commodity markets at this scope and flexibility.

In Chapter 3, the return correlations among Chinese stock market and stock markets in four developed countries, namely the US, UK, France and Japan are modelled with STCC-GARCH and DSTCC-GARCH models. The analysis covers both A-share and B-share indices traded in Chinese stock markets. First of all, using calendar time as a transition variable in the STCC-GARCH model, this Chapter search for evidence of increasing trend in correlation which is expected as a result of reforms in financial markets in China but has not been identified so far. Then, the role of global volatility, index specific volatility and the sign of the news from the indices on the conditional correlations are investigated by considering several measures of these factors as candidate transition variable in the context of STCC-GARCH and DSTCC-GARCH specifications.

Unlike earlier literature, evidences of upward trends are identified and the results show that there are increasing trends in the conditional correlations of Shgh-A index with S&P500, FTSE, CAC and Nikkei indices and Shgh-B with S&P500 and

CAC with the exception of Shgh-B – FTSE and Shgh-B – Nikkei pairs. Not surprisingly, the starting date of increasing trend among indices ranges from 2002 to 2007 supporting the idea that financial reforms that took place in China between 2001-2006 have paved the way of integration of markets in China with the rest of the world particularly after 2002 and hence partially eliminating portfolio diversification benefits since then. Before the transition to the higher levels, the conditional correlations are very close to zero for all index pairs. However, since 2007 the average values of conditional correlations of Shgh-A equal to 0.21, 0.26, 0.298 and 0.315 with S&P500, FTSE, CAC and Nikkei, respectively. On the other hand, for Shgh-B, the conditional correlation increases beyond 0.6 for S&P500 and 0.5 for CAC but it is around 0.26 for FTSE and 0.32 for Nikkei.

Besides, the DSTCC-GARCH models show that the correlation structure is highly affected by market volatility with volatile periods leading to lower correlations compared to the more tranquil periods for A-share index though mixed results are obtained for B-share. The conditional correlations of Shgh-A increase further and reach to 0.296, 0.337 and 0.372 with S&P500, FTSE and CAC during the calm periods of Shgh-A. Similarly, it reaches to 0.621 with Nikkei during the global calm periods. However, for Shgh-B, while increases in the volatility of S&P500, FTSE and CAC lead to rise in the conditional correlation, it decreases with the increase in global volatility and volatility of Nikkei. During calm periods of Nikkei, the conditional correlations of Shgh-B reach to 0.841, 0.371 and 0.373 with S&P500, FTSE and CAC respectively. The correlation with CAC can increase up to 0.522 and 0.655 during the volatile period of S&P500 and CAC, respectively. However these correlation levels are still low relative to the correlation among developed markets and even between developed and developing markets supporting the conclusion that Chinese stock markets, especially A-shares, still offer valuable opportunities to reduce risk. Furthermore, for the first time in the literature, a structural change is detected in the response of conditional correlation between stock markets in China and the US to the lagged standardized errors which are used as default explanatory variables in the correlation equations. This fact along with the strong time trend in the conditional correlation may responsible for the poor performance of the earlier literature.

Chapter 4 models the conditional correlations between stock markets in Turkey and four developed countries, the US, UK, France and Germany via STCC and DSTCC models to assess the potential of Turkish stock market in providing diversification benefits to international investors. As in the third Chapter, the validity of increasing trend in the conditional correlation is tested and the effects of global volatility, index specific volatility and news from indices on the conditional correlations are examined. Besides, time varying conditional correlation of new members, Hungary, Czech Republic, Poland, Bulgaria and Romania, with the US and Germany are estimated by using STCC-GARCH model with time variable to investigate the importance of

membership status on the increasing conditional correlations. The date of membership acceptance is compared with the date of transition from low correlation levels to high levels to see the possible effects of being a member on the conditional correlation. To further clarify this point, the timing of upward trends in the conditional correlations between stock markets in Turkey (which is not a member yet) and Germany are also compared with the timing of those between stock markets in new members and Germany. Moreover, the issue of whether the changes in the conditional correlations are dominated by global factors or EU related developments is also addressed. For this purpose, the timing of upward trends in conditional correlations of stock markets in Turkey and new members with the stock markets in Germany are compared with those of stock markets in Turkey and new members with stock market in the US. If the increase is due to EU related developments then the correlation is expected to increase to higher levels earlier with EU than with the US for all new members and Turkey.

The estimation results of STCC-GARCH models with time being transition variable indicate that the upward trend is valid for conditional correlations of stock markets in Turkey and new members with the developed stock markets in the US, UK, France and Germany but it seems that increasing trends are independent of being a member and cannot solely be attributed to the developments in EU. Since 2005, the average values of conditional correlations of ISX100 equal to 0.553, 0.656, 0.678 and 0.661 with S&P500, FTSE, CAC and DAX, respectively. Besides, estimation results of DSTCC-GARCH models show that the conditional correlations of Turkish stock market with stock markets in EU are highly affected by volatility of Turkish stock market and tend to increase further and reach to 0.799, 0.734 and 0.8 with DAX, CAC and FTSE, respectively during high volatile times in ISX100. On the other hand, the correlation with the stock market in the US is affected by volatility of stock markets in EU and the US. The response of the correlation to volatilities in these markets changes in October 2003. Before this date the conditional correlation tends to increase in turmoil periods and after this date it tends to decline during the turmoil periods. The conditional correlation with S&P500 reaches to 0.677 during low volatility in DAX.

Hence, the correlations of Turkish stock market with developed stock markets are substantially above the correlations of Chinese stock markets implying that stock markets in China have comparative advantage in terms of portfolio diversification.

Chapter 5 investigates the possible effects of the so-called financialization of commodity markets on the correlation structure of commodity markets with the stock markets. The dynamic conditional correlations of two investable commodity index, namely GSCI-S&P agricultural commodity and precious metal sub-indices, are modeled with time varying conditional correlations in the context of STCC-GARCH and

DSTCC-GARCH models. Similarly, this Chapter also search for evidence of increasing trend and analyzes the factors which are capable of explaining the properties and structure of correlation. The estimation results detect evidence of increasing trend in the conditional correlation between precious metal sub-index and S&P500 index. The conditional correlation shifts to the higher correlation levels in October 2008. Before this date, it can be as low as -0.125 and as high as 0.116 according to the news from S&P-PM and volatility of S&P-PM. Since the last quarter of 2008, the conditional correlation is capable to reach 0.725 which is as high as the correlation between developed stock market indices implying significant decline in portfolio diversification benefits. On the other hand, although the average value of correlation between agricultural commodity sub-index and S&P500 has been increasing since 2007, these evidences are not enough to conclude that there is an upward trend in the correlation during the period of financialization of commodity markets. The estimation results uncover that the increase in correlation is not a new phenomenon and cannot be attributed to the recent financial crisis either. Since 1999, it shifts to the higher levels, above 0.6, if both S&P-AG and S&P500 are in volatile phase but return to low levels during tranquil periods. It is also found that measures of global and index specific volatilities determine the dynamic structure of correlation and during turbulence periods the correlation shifts to the higher levels. It seems that current high levels of correlation due to high value of index specific volatilities, may return back to its low levels if the markets become calm.

As a result, this thesis provides a detailed application of STCC-GARCH and DSTCC-GARCH models to examine the structure of return correlations between stock markets in China and major developed countries, stock markets in Turkey and EU countries, and commodity markets and S&P500. The results are quite promising, and showing both rising correlations between markets and uncovering the facts behind the dynamic nature of correlations. There is no doubt that return correlation analysis at sectoral level would be more informative and reveal valuable diversification strategies. However, different content of existing sectoral indices across national stock markets obscure the practical study of correlations among indices at sectoral level.

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APPENDIX A
CCC-GARCH MODEL ESTIMATES

$$\text{Mean Equation} \quad y_{i,t} = \mu_{i0} + \sum_{l=1}^{L_i} \mu_{il} y_{i,t-l} + u_{it}$$

$$\begin{aligned} \text{Variance Equation} \quad H_t &= D_t R_t D_t \\ h_{ii,t} &= \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_{i1} h_{ii,t-1} \end{aligned}$$

$$\text{Correlation Equation} \quad R_{ij,t} = \rho$$

A.1. Estimation Results of CCC Models in Chapter 3

Shgh-A – S&P500

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.158	0.091	0.123	0.855	0.177	0.797	32.73	18.61	125
	(0.108)	(0.031)	(0.032)	(0.238)	(0.03)	(0.031)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.172			0.066	0.077	0.909	27.85	24.96	101
	(0.05)			(0.034)	(0.018)	(0.023)	[0.27]	[0.40]	[0.00]

Correlation Eq.
ρ
0.053
(0.030)

Shgh-A – FTSE

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.171	0.095	0.126	0.869	0.177	0.795	32.43	18.64	125
	(0.111)	(0.033)	(0.032)	(0.245)	(0.028)	(0.031)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.195			0.270	0.129	0.814	27.88	23.67	190
	(0.052)			(0.077)	(0.025)	(0.034)	[0.26]	[0.48]	[0.00]

Correlation Eq.
ρ
0.087
(0.029)

Shgh-A – CAC

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.183	0.088	0.124	0.874	0.176	0.796	32.99	18.69	128
	(0.107)	(0.031)	(0.031)	(0.256)	(0.029)	(0.031)	[0.10]	[0.77]	[0.00]
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.181	-0.07		0.270	0.129	0.814	31.0	17.85	51
	(0.068)	(0.028)		(0.077)	(0.025)	(0.034)	[0.15]	[0.81]	[0.00]

Correlation Eq.
ρ
0.090
(0.029)

Shgh-A – Nikkei

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.168	0.092	0.124	0.882	0.173	0.797	32.51	18.70	125
	(0.107)	(0.033)	(0.030)	(0.259)	(0.029)	(0.031)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.02			0.447	0.133	0.817	27.20	19.77	65
	(0.075)			(0.197)	(0.028)	(0.043)	[0.29]	[0.71]	[0.00]

Correlation Eq.
ρ
0.095
(0.029)

Shgh-B – S&P500

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.022	0.130	0.091	2.548	0.178	0.423	0.31	28.93	32.58	159
(0.154)	(0.034)	(0.03)	(1.06)	(0.039)	(0.117)	(0.1)	[0.22]	[0.11]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.171			0.074	0.086	0.9		26.27	23.36	106
(0.049)			(0.034)	(0.018)	(0.022)		[0.34]	[0.50]	[0.00]

Correlation Eq.
ρ
0.040
(0.031)

Shgh-B – FTSE

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.046	0.132	0.086	2.466	0.174	0.434	0.30	28.51	32.42	161
(0.164)	(0.036)	(0.03)	(1.01)	(0.039)	(0.113)	(0.1)	[0.23]	[0.11]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.184			0.238	0.123	0.828		26.56	25.06	156
(0.057)			(0.076)	(0.023)	(0.032)		[0.33]	[0.40]	[0.00]

Correlation Eq.
ρ
0.11
(0.032)

Shgh-B – CAC

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.032	0.135	0.089	2.555	0.177	0.426	0.30	28.35	32.54	159
(0.160)	(0.032)	(0.03)	(0.961)	(0.039)	(0.117)	(0.1)	[0.23]	[0.11]	[0.00]
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.181	-0.065		0.472	0.152	0.793		31.28	18.0	44
(0.069)	(0.027)		(0.149)	(0.027)	(0.036)		[0.14]	[0.80]	[0.00]

Correlation Eq.
ρ
0.082
(0.031)

Shgh-B – Nikkei

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.04	0.129	0.087	2.519	0.178	0.428	0.30	28.78	32.43	162
(0.162)	(0.036)	(0.03)	(1.04)	(0.039)	(0.118)	(0.1)	[0.22]	[0.11]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.06			0.368	0.125	0.835		25.69	17.95	65
(0.064)			(0.173)	(0.027)	(0.042)		[0.36]	[0.80]	[0.00]

Correlation Eq.
ρ
0.070
(0.036)

A.2. Estimation Results of CCC Models in Chapter 4

ISX100 – DAX

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.537	0.074	0.260	0.06	0.930	32.35	18.98	107
	(0.194)	(0.039)	(0.229)	(0.02)	(0.024)	[0.12]	[0.75]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.189		0.522	0.183	0.779	15.83	15.84	98
	(0.103)		(0.186)	(0.039)	(0.043)	[0.89]	[0.89]	[0.00]

Correlation Eq.
ρ
0.412
(0.032)

ISX100 – CAC

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.541	0.066	0.230	0.065	0.927	32.30	17.35	108
	(0.192)	(0.036)	(0.218)	(0.021)	(0.025)	[0.12]	[0.83]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.154		0.372	0.159	0.805	21.17	15.47	51
	(0.088)		(0.152)	(0.036)	(0.045)	[0.62]	[0.90]	[0.00]

Correlation Eq.
ρ
0.411
(0.032)

ISX100 – FTSE

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.513	0.077	0.175	0.063	0.932	32.08	17.88	108
	(0.178)	(0.036)	(0.188)	(0.02)	(0.022)	[0.12]	[0.81]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.152		0.255	0.115	0.840	15.55	17.31	130
	(0.078)		(0.094)	(0.028)	(0.038)	[0.90]	[0.83]	[0.00]

Correlation Eq.
ρ
0.451
(0.031)

ISX100 – S&P500

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.514	0.059	0.172	0.058	0.939	32.16	13.77	150
	(0.181)	(0.036)	(0.181)	(0.021)	(0.023)	[0.12]	[0.95]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.139		0.049	0.072	0.920	27.79	20.83	69
	(0.073)		(0.034)	(0.016)	(0.018)	[0.27]	[0.65]	[0.00]

Correlation Eq.
ρ
0.380
(0.031)

HTX – DAX

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.347	1.499	0.097	0.808	23.42	31.25	69
	(0.172)	(0.585)	(0.029)	(0.057)	[0.49]	[0.15]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.226	0.245	0.087	0.881	15.27	13.46	160
	(0.112)	(0.099)	(0.025)	(0.032)	[0.91]	[0.96]	[0.00]

Correlation Eq.
ρ
0.556
(0.032)

HTX – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.344	1.801	0.121	0.767	23.90	28.62	60
	(0.174)	(0.611)	(0.032)	(0.057)	[0.47]	[0.23]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.154	0.125	0.081	0.889	26.95	17.37	77
	(0.085)	(0.054)	(0.019)	(0.026)	[0.30]	[0.83]	[0.00]

Correlation Eq.
ρ
0.529
(0.033)

PX – DAX

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.260	0.081	1.840	0.189	0.628	29.16	22.69	64
	(0.105)	(0.034)	(0.662)	(0.055)	(0.105)	[0.21]	[0.53]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.162		0.538	0.168	0.789	16.00	16.45	99
	(0.091)		(0.179)	(0.031)	(0.038)	[0.89]	[0.87]	[0.00]

Correlation Eq.
ρ
0.518
(0.028)

PX – S&P500

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.227	0.088	1.494	0.168	0.682	29.27	20.50	66
	(0.101)	(0.035)	(0.564)	(0.049)	(0.093)	[0.21]	[0.66]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.091		0.073	0.072	0.915	31.12	21.03	62
	(0.068)		(0.038)	(0.017)	(0.020)	[0.15]	[0.64]	[0.00]

Correlation Eq.
ρ
0.483
(0.029)

PTX – DAX

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.318	1.077	0.117	0.815	14.30	28.26	8.8
	(0.140)	(0.315)	(0.023)	(0.033)	[0.94]	[0.25]	[0.01]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.194	0.572	0.182	0.774	15.76	16.21	96
	(0.101)	(0.168)	(0.032)	(0.036)	[0.90]	[0.88]	[0.00]

Correlation Eq.
ρ
0.541
(0.026)

PTX – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.262	0.941	0.109	0.830	14.43	27.59	9.7
	(0.139)	(0.314)	(0.023)	(0.033)	[0.94]	[0.28]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.114	0.085	0.081	0.905	30.85	19.98	64
	(0.076)	(0.045)	(0.018)	(0.022)	[0.16]	[0.69]	[0.00]

Correlation Eq.
ρ
0.516
(0.028)

SOFIX – DAX

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{12}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.228	0.168	0.097	0.790	0.318		0.674	29.46	21.47	276
(0.134)	(0.042)	(0.036)	(0.191)	(0.033)		(0.01)	[0.20]	[0.61]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.227			0.588	0.193	0.758		16.16	16.68	124
(0.104)			(0.186)	(0.041)	(0.05)		[0.88]	[0.86]	[0.00]

Correlation Eq.
ρ
0.159
(0.038)

SOFIX – S&P500

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{12}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.202	0.168	0.099	0.819	0.332		0.663	29.83	21.16	276
(0.138)	(0.045)	(0.043)	(0.380)	(0.064)		(0.06)	[0.19]	[0.63]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.085			0.103	0.088	0.892		24.16	17.12	66
(0.079)			(0.054)	(0.024)	(0.03)		[0.45]	[0.84]	[0.00]

Correlation Eq.
ρ
0.183
(0.039)

BC – DAX

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.415	0.182	0.108	2.72	0.289	0.579	16.67	10.01	300
	(0.142)	(0.046)	(0.045)	(0.98)	(0.056)	(0.087)	[0.86]	[0.99]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.202			0.537	0.184	0.776	15.71	15.87	96
	(0.095)			(0.172)	(0.035)	(0.039)	[0.90]	[0.89]	[0.00]

Correlation Eq.
ρ
0.228
(0.037)

BC – S&P500

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.40	0.168	0.112	2.405	0.284	0.605	15.79	9.85	300
	(0.144)	(0.041)	(0.0475)	(0.97)	(0.058)	(0.087)	[0.89]	[0.99]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.112			0.088	0.080	0.904	30.86	20.12	64
	(0.075)			(0.049)	(0.020)	(0.025)	[0.16]	[0.69]	[0.00]

Correlation Eq.
ρ
0.167
(0.038)

A.3. Estimation Results of CCC Models in Chapter 5

S&P-AG – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.052	0.099	0.06	0.924	24.85	16.64	58
	(0.067)	(0.069)	(0.02)	(0.029)	[0.41]	[0.86]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.191	0.136	0.121	0.857	18.80	18.98	308
	(0.046)	(0.049)	(0.02)	(0.025)	[0.76]	[0.75]	[0.00]

Correlation Eq.
ρ
0.07
(0.031)

S&P-PM – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	-0.004	0.083	0.101	0.883	25.72	12.44	106
	(0.05)	(0.032)	(0.019)	(0.021)	[0.37]	[0.82]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.179	0.069	0.077	0.909	22.07	18.36	130
	(0.046)	(0.036)	(0.019)	(0.024)	[0.57]	[0.78]	[0.00]

Correlation Eq.
ρ
-0.001
(0.035)

APPENDIX B
STCC-GARCH MODEL ESTIMATES

$$\text{Mean Equation} \quad y_{i,t} = \mu_{i0} + \sum_{l=1}^{L_i} \mu_{il} y_{i,t-l} + u_{it}$$

$$\begin{aligned} \text{Variance Equation} \quad H_t &= D_t R_t D_t \\ h_{ii,t} &= \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_{i1} h_{ii,t-1} \end{aligned}$$

$$\begin{aligned} \text{Correlation Eq} \quad R_{ij,t} &= P_{1,ij}(1 - G_t(s_t;\gamma,c) + P_{2,ij} G_t(s_t;\gamma,c) \\ G_t &= (1 + e^{-\gamma(s_t - c)})^{-1} \quad \gamma > 0 \end{aligned}$$

B.1. Estimation Results of STCC Models in Chapter 3

Shgh-A – S&P500

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.163	0.093	0.122	0.848	0.176	0.797	32.64	18.63	124
	(0.103)	(0.032)	(0.032)	(0.256)	(0.029)	(0.032)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.172			0.071	0.08	0.905	27.93	24.61	101
	(0.048)			(0.035)	(0.018)	(0.022)	[0.26]	[0.42]	[0.00]

	Correlation Eq.			
Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.034	0.214	28.36	0.639
	(0.040)	(0.059)	(48)	(0.074)

Shgh-A – FTSE

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.157	0.094	0.125	0.853	0.172	0.799	32.27	18.56	125
	(0.105)	(0.032)	(0.032)	(0.236)	(0.028)	(0.029)	[0.12]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.194			0.271	0.126	0.816	27.95	23.65	188
	(0.054)			(0.073)	(0.024)	(0.033)	[0.26]	[0.48]	[0.00]

.

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.005	0.261	400	0.651
	(0.037)	(0.049)	-	(0.006)

Shgh-A – CAC

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.179	0.089	0.125	0.852	0.172	0.800	32.74	18.62	127
	(0.104)	(0.032)	(0.032)	(0.235)	(0.027)	(0.029)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.180	-0.074		0.507	0.157	0.781	31.02	17.71	50
	(0.071)	(0.031)		(0.143)	(0.027)	(0.036)	[0.15]	[0.82]	[0.00]

.

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.006	0.298	400	0.651
	(0.04)	(0.044)	-	(0.006)

Shgh-A – Nikkei

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.165	0.089	0.119	0.861	0.173	0.798	32.96	18.74	124
	(0.106)	(0.031)	(0.032)	(0.251)	(0.028)	(0.030)	[0.10]	[0.76]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.029			0.428	0.135	0.818	27.21	19.70	64
	(0.080)			(0.176)	(0.027)	(0.039)	[0.29]	[0.71]	[0.00]

.

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.043	0.315	400	0.833
	(0.035)	(0.061)	-	(0.005)

Shgh-B – S&P500

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.024	0.120	0.092	2.459	0.178	0.424	0.31	29.62	32.42	162
(0.152)	(0.040)	(0.036)	(0.929)	(0.038)	(0.115)	(0.10)	[0.19]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.167			0.071	0.086	0.902		26.07	23.48	105
(0.056)			(0.034)	(0.018)	(0.022)		[0.35]	[0.49]	[0.00]

.

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.010	1	18.05	0.983
	(0.047)	-	(16.4)	(0.033)

Shgh-B – FTSE

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.060	0.126	0.089	2.547	0.173	0.426	0.31	29.15	32.17	161
(0.136)	(0.031)	(0.029)	(0.002)	(0.024)	(0.010)	(0.02)	[0.21]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.181			0.242	0.126	0.825		26.55	24.98	157
(0.053)			(0.013)	(0.019)	(0.017)		[0.33]	[0.41]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
A[err.UK]-L2	0.004	0.259	400	1.343
	(0.036)	(0.044)	-	(0.013)

Shgh-B – CAC

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.050	0.131	0.088	2.566	0.176	0.426	0.31	28.87	32.44	159
(0.154)	(0.035)	(0.032)	(1.01)	(0.038)	(0.115)	(0.1)	[0.22]	[0.12]	[0.00]
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.181	-0.069		0.464	0.155	0.792		31.14	18.23	44
(0.077)	(0.033)		(0.146)	(0.028)	(0.036)		[0.15]	[0.79]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
A[serr.US]-L2	0.034	0.370	400	1.32
	(0.034)	(0.072)	-	(0.008)

Shgh-B – Nikkei

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.075	0.128	0.081	2.425	0.179	0.429	0.3	29.04	32.54	163
(0.155)	(0.035)	(0.033)	(0.931)	(0.037)	(0.114)	(0.1)	[0.22]	[0.11]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.055			0.366	0.127	0.834		25.72	17.99	65
(0.082)			(0.166)	(0.027)	(0.039)		[0.37]	[0.80]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
serr.US-L2	0.327	0.033	400	-1.27
	(0.090)	(0.036)	-	(0.04)

B.2. Estimation Results of STCC Models in Chapter 4

ISX100 – DAX

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.497	0.082	0.536	0.066	0.916	32.79	20.77	104
	(0.180)	(0.038)	(0.299)	(0.019)	(0.024)	[0.11]	[0.65]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.194		0.535	0.164	0.796	15.67	16.48	97
	(0.098)		(0.186)	(0.035)	(0.041)	[0.90]	[0.87]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.275	0.657	400	0.685
	(0.041)	(0.033)	-	(0.005)

ISX100 – CAC

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.569	0.076	0.496	0.072	0.912	32.51	18.34	103
	(0.173)	(0.035)	(0.279)	(0.019)	(0.024)	[0.11]	[0.78]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.154		0.387	0.149	0.816	21.05	15.65	51
	(0.091)		(0.152)	(0.034)	(0.042)	[0.63]	[0.90]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.245	0.675	37.9	0.679
	(0.043)	(0.035)	(40)	(0.028)

ISX100 – FTSE

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.498	0.075	0.405	0.067	0.918	32.56	18.57	104
	(0.178)	(0.035)	(0.269)	(0.02)	(0.025)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.154		0.238	0.105	0.855	15.72	18.34	130
	(0.079)		(0.088)	(0.025)	(0.034)	[0.90]	[0.78]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.295	0.656	34.5	0.655
	(0.047)	(0.035)	(28)	(0.037)

ISX100 – S&P500

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.510	0.086	0.512	0.076	0.908	32.40	18.37	101
	(0.184)	(0.036)	(0.302)	(0.022)	(0.027)	[0.12]	[0.78]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.123		0.073	0.079	0.911	30.67	19.99	64
	(0.076)		(0.039)	(0.017)	(0.020)	[0.16]	[0.70]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.203	0.546	400	0.566
	(0.048)	(0.036)	-	(0.005)

HTX – DAX

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.319	1.012	0.086	0.852	23.37	32.40	81
	(0.180)	(0.486)	(0.027)	(0.049)	[0.49]	[0.12]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.241	0.251	0.083	0.881	15.15	13.66	155
	(0.113)	(0.108)	(0.025)	(0.033)	[0.91]	[0.95]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.404	0.698	16.91	0.756
	(0.083)	(0.071)	(14.35)	(0.071)

HTX – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.328	1.655	0.125	0.774	24.05	27.51	60
	(0.169)	(0.556)	(0.031)	(0.055)	[0.46]	[0.28]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.164	0.119	0.082	0.888	27.01	16.91	78
	(0.078)	(0.047)	(0.017)	(0.023)	[0.30]	[0.85]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.341	0.802	5.53	0.85
	(0.457)	(0.734)	(16.3)	(0.433)

PX – DAX

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.235	0.079	1.690	0.176	0.659	29.48	21.97	65
	(0.114)	(0.034)	(0.795)	(0.067)	(0.133)	[0.20]	[0.58]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.174		0.611	0.167	0.779	15.88	17.13	95
	(0.101)		(0.187)	(0.032)	(0.038)	[0.89]	[0.84]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.429	0.655	400	0.691
	(0.038)	(0.031)	-	(0.007)

PX – S&P500

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.229	0.076	1.662	0.177	0.659	29.67	21.91	65
	(0.101)	(0.034)	(0.619)	(0.051)	(0.098)	[0.20]	[0.58]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.086		0.106	0.078	0.904	30.72	21.56	61
	(0.068)		(0.049)	(0.018)	(0.023)	[0.16]	[0.60]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.339	0.566	29.15	0.488
	(0.067)	(0.034)	(33)	(0.059)

PTX – DAX

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.300	1.125	0.118	0.811	14.27	28.55	8.66
	(0.129)	(0.345)	(0.024)	(0.035)	[0.94]	[0.24]	[0.01]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.186	0.597	0.177	0.776	15.80	16.60	96
	(0.095)	(0.183)	(0.033)	(0.037)	[0.90]	[0.86]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.476	0.797	12.21	0.848
	(0.044)	(0.232)	(14)	(0.136)

PTX – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.255	1.034	0.109	0.824	14.36	28.27	9.38
	(0.141)	(0.321)	(0.023)	(0.033)	[0.94]	[0.25]	[0.01]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.110	0.102	0.083	0.900	30.61	20.35	63
	(0.078)	(0.045)	(0.018)	(0.022)	[0.16]	[0.68]	[0.00]

Correlation Eq.

Transition Variable	ρ_1	ρ_2	γ	c
Time	0.446	0.561	400	0.496
	(0.052)	(0.033)	-	(0.012)

SOFIX – DAX

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{12}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.195	0.167	0.109	0.742	0.295		0.69	28.60	22.42	280
(0.125)	(0.042)	(0.039)	(0.346)	(0.057)		(0.06)	[0.24]	[0.55]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.278			0.522	0.181	0.775		15.52	15.82	122
(0.102)			(0.186)	(0.038)	(0.05)		[0.90]	[0.89]	[0.00]

Correlation Eq.

Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.002	0.469	400	0.801
	(0.058)	(0.055)	-	(0.005)

SOFIX – S&P500

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{12}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.163	0.169	0.104	0.879	0.329		0.66	29.87	21.78	275
(0.129)	(0.042)	(0.039)	(0.365)	(0.061)		(0.06)	[0.19]	[0.59]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.099			0.108	0.088	0.891		24.05	17.35	66
(0.076)			(0.053)	(0.022)	(0.03)		[0.46]	[0.83]	[0.00]

Correlation Eq.

Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.147	0.440	6.72	0.632
	(0.97)	(0.252)	(16)	(0.536)

BC – DAX

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.408	0.133	0.119	1.48	0.237	0.700	14.53	9.48	300
	(0.132)	(0.046)	(0.041)	(0.89)	(0.055)	(0.089)	[0.93]	[0.99]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.197			0.292	0.137	0.815	15.09	16.49	132
	(0.074)			(0.09)	(0.028)	(0.036)	[0.92]	[0.87]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.064	0.603	400	0.796
	(0.045)	(0.044)	-	(0.003)

BC – S&P500

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.352	0.145	0.107	2.064	0.245	0.654	15.85	9.74	300
	(0.128)	(0.041)	(0.042)	(0.95)	(0.056)	(0.091)	[0.89]	[0.99]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.135			0.086	0.082	0.905	30.77	19.76	64
	(0.073)			(0.05)	(0.019)	(0.023)	[0.16]	[0.71]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.004	1	9.76	0.897
	(0.06)	-	(3.49)	(0.023)

B.3. Estimation Results of STCC Models in Chapter 5

S&P-AG – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.065	0.064	0.043	0.947	25.81	19.81	20
	(0.066)	(0.045)	(0.017)	(0.023)	[0.36]	[0.71]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.173	0.071	0.076	0.909	22.06	18.30	130
	(0.053)	(0.032)	(0.016)	(0.021)	[0.57]	[0.79]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	0.007	0.458	400	0.89
	(0.034)	(0.075)	-	(0.004)

S&P-PM – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	-0.002	0.085	0.104	0.88	25.71	12.49	106
	(0.051)	(0.025)	(0.012)	(0.012)	[0.36]	[0.82]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.164	0.07	0.076	0.909	22.08	18.35	130
	(0.053)	(0.025)	(0.015)	(0.017)	[0.57]	[0.79]	[0.00]

Correlation Eq.				
Transition Variable	ρ_1	ρ_2	γ	c
Time	-0.10	0.161	400	0.662
	(0.036)	(0.046)	-	(0.005)

APPENDIX C
DSTCC-GARCH MODEL ESTIMATES

$$\text{Mean Equation} \quad y_{i,t} = \mu_{i0} + \sum_{l=1}^{L_i} \mu_{il} y_{i,t-l} + u_{it}$$

$$\begin{aligned} \text{Variance Equation} \quad H_t &= D_t R_t D_t \\ h_{ii,t} &= \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_{i1} h_{ii,t-1} \end{aligned}$$

$$\begin{aligned} \text{Correlation Eq} \quad R_t &= (1 - G_{2,t})[(1 - G_{1,t})P_{11} + G_{1,t}P_{21}] \\ &\quad + G_{2,t}[(1 - G_{1,t})P_{12} + G_{1,t}P_{22}] \\ G_{m,t} &= (1 + e^{-\gamma_m(s_{m,t} - c_m)})^{-1} \quad \gamma > 0, \ and \ m = 1, 2 \end{aligned}$$

C.1. Estimation Results of DSTCC Models in Chapter 3

Shgh-A – S&P500

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.159	0.083	0.123	0.836	0.174	0.80	33.37	18.71	125
	(0.077)	(0.003)	(0.001)	(0.070)	(0.011)	(0.011)	[0.10]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.181			0.07	0.08	0.906	27.92	24.58	101
	(0.001)			(0.001)	(0.003)	(0.003)	[0.26]	[0.43]	[0.00]
⋮									

	Correlation Eq.							
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[serr.Ch]-L2	0.052	-0.166	0.296	0.089	71.27	400	0.632	0.798
	(0.04)	(0.041)	(0.056)	(0.06)	(13)	-	(0.039)	(0.015)

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.157	0.104	0.122	0.845	0.175	0.798	31.81	18.44	125
	(0.035)	(0.001)	(0.004)	(0.036)	(0.018)	(0.016)	[0.13]	[0.78]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.187			0.07	0.08	0.907	27.91	24.53	101
	(0.004)			(0.001)	(0.004)	(0.004)	[0.26]	[0.43]	[0.00]
⋮									

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.Ch-L1	0.128	-0.149	0.202	0.312	17.33	400	0.727	0.005
	(0.003)	(0.031)	(0.022)	(0.1)	(16)	-	(0.071)	(0.001)

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.184	0.10	0.116	0.888	0.178	0.795	32.46	18.77	125
	(0.104)	(0.032)	(0.032)	(0.056)	(0.007)	(0.006)	[0.11]	[0.76]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.163			0.07	0.08	0.909	27.87	24.97	101
	(0.054)			(0.009)	(0.004)	(0.003)	[0.26]	[0.41]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.US-L1	-0.19	0.063	0.210	0.275	14.51	400	0.666	-0.087
	(0.061)	(0.062)	(0.095)	(0.065)	(9.5)	-	(0.089)	(0.03)

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.161	0.091	0.12	0.85	0.174	0.799	32.75	18.66	125
	(0.107)	(0.031)	(0.032)	(0.189)	(0.019)	(0.017)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.169			0.07	0.08	0.908	27.89	24.83	101
	(0.054)			(0.03)	(0.017)	(0.02)	[0.26]	[0.41]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + VIX-L1	0.035	-0.177	1	1	5.254	400	1	20.23
	(0.08)	(0.144)	-	-	(4.9)	-	(0.089)	(0.164)

Shgh-A – FTSE

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.151	0.092	0.137	0.885	0.173	0.798	32.25	18.45	127
	(0.084)	(0.001)	(0.002)	(0.073)	(0.008)	(0.006)	[0.12]	[0.78]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.173			0.271	0.123	0.819	28.08	23.54	188
	(0.003)			(0.027)	(0.006)	(0.007)	[0.25]	[0.49]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[serr.Ch]-L2	0.04	-0.119	0.337	0.126	400	400	0.651	1.058
	(0.04)	(0.066)	(0.038)	(0.06)	-	-	(0.005)	(0.024)

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.158	0.092	0.125	0.863	0.176	0.798	32.60	18.56	125
	(0.001)	(0.004)	(0.004)	(0.011)	(0.008)	(0.007)	[0.11]	[0.78]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.195			0.271	0.129	0.815	27.90	23.65	190
	(0.003)			(0.014)	(0.006)	(0.007)	[0.26]	[0.48]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.Ch-L4	-0.087	0.048	0.122	0.372	400	400	0.652	-0.428
	(0.051)	(0.043)	(0.05)	(0.05)	-	-	(0.005)	(0.013)

Shgh-A – CAC

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.174	0.087	0.127	0.854	0.174	0.798	32.68	18.63	128
	(0.084)	(0.004)	(0.001)	(0.051)	(0.007)	(0.006)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.179	-0.072		0.516	0.163	0.774	31.35	18.01	52
	(0.003)	(0.001)		(0.026)	(0.01)	(0.007)	[0.14]	[0.80]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[serr.Ch]-L2	0.05	-0.116	0.372	0.162	400	400	0.651	0.906
	(0.034)	(0.02)	(0.007)	(0.056)	-	-	(0.005)	(0.04)

Shgh-A – Nikkei

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.171	0.094	0.121	0.854	0.174	0.798	32.57	18.69	125
	(0.105)	(0.031)	(0.032)	(0.242)	(0.03)	(0.03)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.006			0.436	0.134	0.819	27.27	19.72	66
	(0.081)			(0.175)	(0.026)	(0.039)	[0.29]	[0.71]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.HK-L2	0.082	-0.184	0.352	-0.018	400	400	0.804	0.844
	(0.04)	(0.087)	(0.066)	(0.165)	-	-	(0.01)	(0.024)

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.137	0.089	0.116	0.878	0.175	0.796	33.10	18.62	124
	(0.115)	(0.031)	(0.032)	(0.234)	(0.028)	(0.03)	[0.10]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.048			0.428	0.131	0.821	27.11	19.69	64
	(0.077)			(0.184)	(0.027)	(0.041)	[0.30]	[0.71]	[0.00]

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Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + VIX-L3	0.059	0.002	0.621	0.198	400	400	0.834	21.57
	(0.042)	(0.06)	(0.076)	(0.089)	-	-	(0.003)	(0.022)

	Mean Eq			Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.164	0.095	0.117	0.875	0.175	0.797	32.67	18.69	125
	(0.105)	(0.034)	(0.032)	(0.244)	(0.028)	(0.03)	[0.11]	[0.77]	[0.00]
(2)	μ_{20}			α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.033			0.428	0.134	0.819	27.19	19.69	65
	(0.08)			(0.081)	(0.015)	(0.005)	[0.29]	[0.71]	[0.00]

.

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.HK]-L3	0.053	-0.067	0.397	0.024	400	400	0.834	5.933
	(0.036)	(0.14)	(0.064)	(0.162)	-	-	(0.005)	(0.131)

Shgh-B – S&P500

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.008	0.125	0.087	2.466	0.181	0.402	0.33	29.09	32.59	162
(0.152)	(0.035)	(0.032)	(0.934)	(0.038)	(0.115)	(0.10)	[0.22]	[0.11]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.162			0.066	0.083	0.906		25.99	23.83	104
(0.056)			(0.031)	(0.017)	(0.021)		[0.35]	[0.47]	[0.00]

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Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Jap]-L3	-0.029	-0.057	0.841	0.111	8.97	400	0.899	1.77
	(0.07)	(0.08)	(1.287)	(0.425)	(13.3)	-	(0.359)	(0.03)

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.037	0.126	0.095	2.556	0.179	0.422	0.31	29.07	32.31	160
(0.148)	(0.037)	(0.034)	(1.045)	(0.039)	(0.121)	(0.10)	[0.22]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.162			0.066	0.083	0.906		25.99	23.83	104
(0.056)			(0.033)	(0.017)	(0.021)		[0.35]	[0.47]	[0.00]

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Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + Time	-0.08	0.074	-	0.465	400	400	0.436	0.912
	(0.055)	(0.044)	-	(0.092)	-	-	(0.008)	(0.005)

Shgh-B – FTSE

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.079	0.133	0.086	2.574	0.171	0.433	0.3	28.59	32.14	160
(0.138)	(0.032)	(0.028)	(0.016)	(0.027)	(0.012)	(0.10)	[0.23]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.181			0.240	0.127	0.825		26.50	25.00	158
(0.053)			(0.019)	(0.011)	(0.007)		[0.33]	[0.41]	[0.00]

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Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2+serr.HK-L2	0.062	-0.309	0.298	0.116	400	400	1.27	0.59
	(0.044)	(0.109)	(0.046)	(0.105)	-	-	(0.024)	(0.009)

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.05	0.123	0.086	2.61	0.174	0.422	0.31	29.45	32.17	162
(0.146)	(0.035)	(0.031)	(0.533)	(0.021)	(0.017)	(0.03)	[0.20]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.186			0.238	0.126	0.826		26.47	25.00	159
(0.055)			(0.032)	(0.011)	(0.005)		[0.33]	[0.41]	[0.00]

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Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2+serr.US-L2	0.066	-0.198	0.273	0.294	400	400	1.68	0.744
	(0.043)	(0.107)	(0.056)	(0.1)	-	-	(0.038)	(0.017)

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.078	0.121	0.09	2.475	0.170	0.423	0.31	29.65	32.09	162
(0.155)	(0.007)	(0.015)	(0.001)	(0.024)	(0.011)	(0.02)	[0.20]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.182			0.243	0.125	0.825		26.56	24.97	157
(0.022)			(0.042)	(0.016)	(0.02)		[0.33]	[0.41]	[0.00]

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Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2+S[serr.US]-L2	0.061	-0.111	0.171	0.312	400	400	1.266	0.549
	(0.059)	(0.007)	(0.048)	(0.022)	-	-	(0.016)	(0.01)

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.065	0.128	0.085	2.63	0.175	0.420	0.31	28.99	32.16	161
(0.13)	(0.027)	(0.026)	(0.001)	(0.013)	(0.017)	(0.01)	[0.22]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.184			0.245	0.124	0.825		26.60	24.96	155
(0.045)			(0.029)	(0.01)	(0.005)		[0.32]	[0.41]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2+VIX-L3	0.066	-0.139	0.284	0.217	400	400	1.27	21.57
	(0.046)	(0.061)	(0.057)	(0.063)	-	-	(0.012)	(0.035)

Shgh-B – CAC

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.061	0.126	0.091	2.484	0.179	0.414	0.32	28.29	32.51	160
(0.152)	(0.035)	(0.033)	(0.982)	(0.037)	(0.108)	(0.1)	[0.21]	[0.11]	[0.00]
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.157	-0.07		0.449	0.151	0.797		31.24	18.13	44
(0.077)	(0.032)		(0.145)	(0.027)	(0.036)		[0.15]	[0.80]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2+Time	-0.044	0.315	0.213	0.522	400	400	1.32	0.735
	(0.043)	(0.1)	(0.062)	(0.089)	-	-	(0.01)	(0.007)

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.039	0.133	0.079	2.547	0.169	0.428	0.31	28.77	32.44	160
(0.129)	(0.033)	(0.028)	(0.077)	(0.002)	(0.007)	(0.1)	[0.23]	[0.11]	[0.00]
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.195	-0.057		0.468	0.158	0.789		31.26	18.31	44
(0.069)	(0.001)		(0.045)	(0.01)	(0.008)		[0.15]	[0.79]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2+A[serr.Fr]-L1	-0.004	0.123	0.29	0.655	400	400	1.32	1.05
	(0.005)	(0.059)	(0.076)	(0.061)	-	-	(0.005)	(0.02)

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.068	0.129	0.084	2.755	0.182	0.418	0.30	29.14	32.42	161
(0.151)	(0.034)	(0.032)	(1.049)	(0.038)	(0.118)	(0.1)	[0.21]	[0.12]	[0.00]
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.189	-0.072		0.462	0.154	0.793		31.04	18.21	44
(0.077)	(0.032)		(0.149)	(0.028)	(0.036)		[0.15]	[0.79]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2+A[err.Jap]-L3	0.062	-0.27	0.373	-0.622	400	400	1.32	4.71
	(0.036)	(0.118)	(0.074)	(0.168)	-	-	(0.008)	(0.028)

Shgh-B – Nikkei

Mean Eq			Volatility Eq				Diagnostics		
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
0.081	0.126	0.079	2.591	0.181	0.428	0.3	29.31	32.42	166
(0.151)	(0.036)	(0.032)	(0.813)	(0.031)	(0.111)	(0.1)	[0.21]	[0.12]	[0.00]
μ_{20}			α_{20}	α_{21}	β_{21}		LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
0.057			0.383	0.127	0.832		25.68	17.96	65
(0.082)			(0.134)	(0.021)	(0.027)		[0.37]	[0.80]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
serr.US-L2+err.Jap-L4	0.102	0.317	-0.375	0.069	400	400	-1	-3.66
	(0.252)	(0.077)	(0.082)	(0.039)	-	-	(0.015)	(0.195)

C.2. Estimation Results of DSTCC Models in Chapter 4

ISX100 – DAX

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.611	0.051	0.676	0.081	0.899	32.86	13.54	105
	(0.036)	(0.019)	(0.036)	(0.004)	(0.004)	[0.11]	[0.96]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.261		0.664	0.191	0.757	16.17	16.50	95
	(0.001)		(0.018)	(0.008)	(0.006)	[0.88]	[0.87]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.Tr-L2	0.626	0.221	0.805	0.636	400	400	0.685	-1.21
	(0.029)	(0.032)	(0.049)	(0.029)	-	-	(0.011)	(0.064)

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.515	0.053	0.494	0.066	0.919	32.77	14.95	104
	(0.139)	(0.005)	(0.365)	(0.026)	(0.035)	[0.11]	[0.92]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.234		0.594	0.173	0.781	16.11	16.44	95
	(0.001)		(0.181)	(0.027)	(0.034)	[0.88]	[0.87]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Tr]-L2	0.187	0.539	0.652	0.739	400	307	0.685	8.58
	(0.044)	(0.055)	(0.03)	(0.101)	-	1614	(0.004)	(0.154)

ISX100 – CAC

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.607	0.039	0.641	0.082	0.899	32.97	13.32	104
	(0.042)	(0.001)	(0.018)	(0.005)	(0.006)	[0.11]	[0.96]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.184		0.462	0.167	0.793	18.54	17.07	51
	(0.007)		(0.017)	(0.01)	(0.012)	[0.78]	[0.85]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.Tr-L2	0.672	0.159	0.899	0.678	24.7	17.5	0.664	-8.86
	(0.042)	(0.041)	(0.058)	(0.03)	(4.46)	(2.3)	(0.022)	(0.118)

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.608	0.062	0.623	0.083	0.90	32.55	13.26	104
	(0.132)	(0.003)	(0.187)	(0.017)	(0.018)	[0.11]	[0.96]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.222		0.465	0.172	0.791	18.27	17.16	51
	(0.047)		(0.11)	(0.031)	(0.035)	[0.79]	[0.84]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Tr]-L2	0.145	0.635	0.681	0.734	29.4	141	0.661	9.06
	(0.044)	(0.052)	(0.035)	(0.115)	(20)	(36)	(0.029)	(0.136)

ISX100 – FTSE

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.498	0.075	0.397	0.067	0.92	32.46	14.17	105
	(0.125)	(0.003)	(0.081)	(0.013)	(0.013)	[0.11]	[0.94]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.181		0.279	0.123	0.833	14.96	19.41	131
	(0.007)		(0.048)	(0.016)	(0.019)	[0.92]	[0.73]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Tr]-L2	0.185	0.587	0.649	0.799	26.4	130	0.626	9.05
	(0.044)	(0.061)	(0.035)	(0.065)	(16.8)	(16.2)	(0.029)	(0.024)

ISX100 – S&P500

	Mean Eq		Volatility Eq			Diagnostics		
(1)	μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.523	0.064	0.568	0.083	0.903	32.62	13.51	103
	(0.182)	(0.032)	(0.341)	(0.025)	(0.03)	[0.11]	[0.96]	[0.00]
(2)	μ_{20}		α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.144		0.089	0.082	0.906	27.59	20.55	63
	(0.074)		(0.041)	(0.017)	(0.019)	[0.28]	[0.66]	[0.00]

	Correlation Eq.							
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Ger]-L1	-0.115	0.272	0.677	0.514	400	400	0.566	0.71
	(0.117)	(0.044)	(0.051)	(0.045)	-	-	(0.005)	(0.02)

C.3. Estimation Results of DSTCC Models in Chapter 5

S&P-AG – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.053	0.085	0.051	0.935	25.71	19.26	20
	(0.066)	(0.011)	(0.001)	(0.002)	[0.36]	[0.73]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.181	0.07	0.077	0.909	22.06	18.33	130
	(0.053)	(0.009)	(0.003)	(0.003)	[0.57]	[0.79]	[0.00]

	Correlation Eq.							
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + vol.S&P-L2	-0.003	0.485	0.357	0.646	400	400	0.889	9.99
	(0.027)	(0.117)	(0.093)	(0.086)	-	-	(0.008)	(1.546)

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.064	0.075	0.045	0.942	25.77	19.49	20
	(0.067)	(0.059)	(0.017)	(0.026)	[0.36]	[0.73]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.177	0.085	0.086	0.897	21.96	16.90	134
	(0.053)	(0.038)	(0.019)	(0.024)	[0.58]	[0.85]	[0.00]

	Correlation Eq.							
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + VIX-L2	-0.022	0.235	0.369	0.580	277	400	0.894	27.98
	(0.033)	(0.094)	(0.116)	(0.104)	(241)	-	(0.007)	(0.669)

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.063	0.084	0.051	0.935	25.69	19.22	20
	(0.066)	(0.011)	(0.002)	(0.002)	[0.37]	[0.74]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.177	0.071	0.077	0.909	22.06	18.33	130
	(0.05)	(0.005)	(0.001)	(0.001)	[0.57]	[0.79]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
vol.AG-L4 + vol.S&P-L2	-0.052	0.053	0.139	0.621	400	400	5.59	7.72
	(0.007)	(0.104)	(0.046)	(0.054)	-	-	(0.096)	(0.68)

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	0.071	0.083	0.05	0.935	25.67	19.09	20
	(0.065)	(0.011)	(0.003)	(0.002)	[0.36]	[0.74]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.171	0.071	0.077	0.909	22.07	18.29	130
	(0.053)	(0.008)	(0.002)	(0.002)	[0.58]	[0.79]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
vol.AG-L4 + VIX-L2	-0.043	0.079	0.105	0.573	400	400	5.87	27.98
	(0.039)	(0.105)	(0.053)	(0.064)	-	-	(0.344)	(600)

S&P-PM – S&P500

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	-0.002	0.079	0.099	0.886	25.69	12.43	108
	(0.051)	(0.03)	(0.016)	(0.018)	[0.36]	[0.82]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.176	0.077	0.077	0.906	21.99	17.93	130
	(0.01)	(0.032)	(0.014)	(0.017)	[0.58]	[0.80]	[0.00]

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.PM-L2	-0.089	0.116	0.155	0.585	400	400	0.897	1.507
	(0.035)	(0.066)	(0.107)	(0.076)	-	-	(0.005)	(0.011)

	Mean Eq	Volatility Eq			Diagnostics		
(1)	μ_{10}	α_{10}	α_{11}	β_{11}	LB(ε_1,24)	LB(ε_1^2,24)	JB(ε_1)
	-0.003	0.081	0.102	0.884	25.68	12.46	108
	(0.046)	(0.009)	(0.005)	(0.004)	[0.36]	[0.82]	[0.00]
(2)	μ_{20}	α_{20}	α_{21}	β_{21}	LB(ε_2,24)	LB(ε_2^2,24)	JB(ε_2)
	0.159	0.071	0.076	0.909	22.09	18.26	130
	(0.001)	(0.005)	(0.003)	(0.003)	[0.57]	[0.79]	[0.00]

Correlation Eq.								
Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.PM]-L4	-0.125	0.035	0.725	0.228	400	396	0.896	1.349
	(0.039)	(0.046)	(0.046)	(0.02)	-	(100)	(0.005)	(0.01)

APPENDIX D
STCC-GARCH MODEL ESTIMATES NOT REPORTED IN CHAPTERS

D.1. Estimation Results of STCC Models not reported in Chapter 3

Shgh-A – S&P500

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.157	0.093	0.122	0.867	0.178	0.795
	(0.104)	(0.025)	(0.023)	(0.084)	(0.008)	(0.006)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.171			0.067	0.078	0.909
	(0.023)			(0.001)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Ch]-L2	-4938.10	0.212	0.011	400	0.909
		(0.067)	(0.037)	-	(0.044)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.149	0.095	0.125	0.862	0.178	0.795
	(0.084)	(0.024)	(0.018)	(0.074)	(0.008)	(0.006)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.165			0.067	0.078	0.909
	(0.026)			(0.001)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Ch]-L2	-4936.41	0.146	-0.05	400	0.661
		(0.037)	(0.05)	-	(0.043)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.152	0.093	0.115	0.862	0.176	0.796
	(0.104)	(0.019)	(0.044)	(0.084)	(0.008)	(0.006)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.165			0.067	0.078	0.909
	(0.057)			(0.001)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Ch]-L2	-4936.55	0.142	-0.053	103	0.449
		(0.041)	(0.05)	(280)	(0.059)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.161	0.088	0.118	0.858	0.179	0.795
	(0.103)	(0.005)	(0.004)	(0.084)	(0.008)	(0.006)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.174			0.067	0.078	0.909
	(0.009)			(0.01)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.Ch-L1	-4935.83	0.164	-0.049	400	-0.008
		(0.046)	(0.04)	-	(0.02)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.172	0.096	0.117	0.867	0.176	0.797
	(0.112)	(0.033)	(0.034)	(0.12)	(0.032)	(0.03)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.161			0.067	0.078	0.909
	(0.055)			(0.013)	(0.005)	(0.009)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.US-L1	-4938.11	-0.042	0.125	400	-0.228
		(0.052)	(0.04)	-	(0.052)

Shgh-A – FTSE

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.173	0.095	0.126	0.872	0.178	0.795
	(0.103)	(0.031)	(0.032)	(0.083)	(0.008)	(0.006)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.194			0.271	0.129	0.814
	(0.044)			(0.016)	(0.007)	(0.005)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Ch]-L2	-4945.75	0.147	-0.013	400	0.906
		(0.036)	(0.048)	-	(0.111)

Shgh-A – CAC

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.184	0.083	0.126	0.905	0.176	0.794
	(0.106)	(0.033)	(0.032)	(0.266)	(0.029)	(0.032)
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}
	0.185	-0.069		0.507	0.166	0.774
	(0.073)	(0.031)		(0.142)	(0.029)	(0.038)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Ch]-L2	-5174.87	0.131	-0.155	400	7.55
		(0.032)	(0.079)	-	(2.66)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.184	0.088	0.124	0.878	0.176	0.796
	(0.104)	(0.031)	(0.029)	(0.083)	(0.008)	(0.006)
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}
	0.181	-0.07		0.515	0.163	0.775
	(0.064)	(0.031)		(0.046)	(0.01)	(0.008)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Ch]-L2	-5176.49	0.151	-0.018	400	0.907
		(0.037)	(0.05)	-	(0.084)

Shgh-A – Nikkei

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.161	0.095	0.125	0.877	0.174	0.798
	(0.106)	(0.031)	(0.032)	(0.248)	(0.003)	(0.031)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.007			0.450	0.134	0.817
	(0.08)			(0.181)	(0.026)	(0.04)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.HK-L2	-5235.59	0.133	-0.142	400	3.77
		(0.032)	(0.078)	-	(0.214)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.172	0.096	0.124	0.876	0.173	0.798
	(0.107)	(0.034)	(0.032)	(0.254)	(0.027)	(0.030)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.007			0.454	0.135	0.815
	(0.080)			(0.185)	(0.027)	(0.041)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.HK-L2	-5235.65	0.141	-0.144	400	0.844
		(0.032)	(0.085)	-	(0.028)

Shgh-B – S&P500

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.059	0.125	0.086	2.587	0.179	0.421	0.305
(0.001)	(0.032)	(0.034)	(0.001)	(0.023)	(0.027)	(0.026)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.177			0.073	0.085	0.902	
(0.045)			(0.029)	(0.001)	(0.004)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.US-L2	-4775.72	0.103	-0.097	400	0.734
		(0.014)	(0.026)	-	(0.018)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.056	0.125	0.085	2.496	0.179	0.434	0.297
(0.142)	(0.035)	(0.029)	(0.167)	(0.004)	(0.008)	(0.007)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.174			0.073	0.086	0.901	
(0.053)			(0.009)	(0.004)	(0.003)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.US-L2	-4776.34	0.101	-0.084	400	0.312
		(0.031)	(0.052)	-	(0.029)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.051	0.127	0.086	2.637	0.181	0.425	0.299
(0.149)	(0.036)	(0.033)	(1.047)	(0.038)	(0.111)	(0.099)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.171			0.075	0.088	0.898	
(0.057)			(0.033)	(0.018)	(0.022)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.HK-L2	-4776.94	0.08	-0.111	400	1.764
		(0.034)	(0.063)	-	(0.017)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.057	0.129	0.086	2.715	0.180	0.428	0.294
(0.153)	(0.036)	(0.032)	(1.040)	(0.037)	(0.108)	(0.102)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.129			0.072	0.087	0.901	
(0.036)			(0.021)	(0.007)	(0.005)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.HK-L2	-4775.88	0.091	-0.122	400	0.486
		(0.039)	(0.063)	-	(0.017)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.018	0.131	0.088	2.502	0.178	0.428	0.304
(0.154)	(0.036)	(0.033)	(1.004)	(0.039)	(0.129)	(0.107)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.131			0.072	0.086	0.902	
(0.036)			(0.032)	(0.017)	(0.021)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Jap]-L3	-4777.85	0.098	-0.028	400	1.732
		(0.044)	(0.049)	-	(0.037)

Shgh-B – FTSE

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.034	0.126	0.091	2.369	0.171	0.429	0.314
(0.152)	(0.035)	(0.032)	(0.916)	(0.035)	(0.107)	(0.096)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.179			0.226	0.120	0.834	
(0.057)			(0.071)	(0.026)	(0.033)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
Time	-4775.47	0.048	0.909	11.79	11.79
		(0.040)	(2.539)	(14.98)	(14.98)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.061	0.136	0.083	2.549	0.173	0.433	0.301
(0.138)	(0.031)	(0.029)	(0.002)	(0.010)	(0.008)	(0.008)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.195			0.238	0.124	0.827	
(0.053)			(0.015)	(0.007)	(0.005)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.UK-L2	-4774.37	0.218	-0.019	400	-0.009
		(0.038)	(0.046)	-	(0.019)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.024	0.131	0.098	2.349	0.191	0.427	0.305
(0.146)	(0.019)	(0.029)	(0.001)	(0.022)	(0.014)	(0.022)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.201			0.221	0.122	0.833	
(0.048)			(0.038)	(0.013)	(0.008)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.UK]-L1	-4780.34	-0.022	0.179	400	0.686
		(0.135)	(0.175)	-	(0.137)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.056	0.125	0.086	2.518	0.174	0.434	0.302
(0.141)	(0.033)	(0.029)	(0.018)	(0.008)	(0.008)	(0.007)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.183			0.238	0.123	0.827	
(0.053)			(0.016)	(0.007)	(0.005)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.UK]-L2	-4775.41	0.048	0.266	400	0.854
		(0.018)	(0.048)	-	(0.048)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.055	0.138	0.093	2.438	0.171	0.431	0.305
(0.155)	(0.039)	(0.032)	(0.021)	(0.007)	(0.008)	(0.007)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.184			0.239	0.123	0.828	
(0.057)			(0.016)	(0.007)	(0.005)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.UK]-L2	-4775.97	0.011	0.226	400	0.391
		(0.015)	(0.045)	-	(0.035)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.067	0.121	0.088	2.307	0.169	0.431	0.315
(0.152)	(0.036)	(0.032)	(0.878)	(0.035)	(0.108)	(0.096)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.178			0.231	0.124	0.830	
(0.057)			(0.071)	(0.023)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.US-L2	-4773.87	0.374	0.056	400	-2.109
		(0.070)	(0.035)	-	(0.024)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.071	0.125	0.084	2.267	0.168	0.432	0.316
(0.153)	(0.036)	(0.032)	(0.919)	(0.034)	(0.108)	(0.101)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.179			0.232	0.123	0.830	
(0.057)			(0.071)	(0.023)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.US-L2	-4776.02	0.358	0.069	400	-1.226
		(0.078)	(0.034)	-	(0.005)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.067	0.126	0.087	2.431	0.172	0.438	0.302
(0.153)	(0.036)	(0.032)	(1.016)	(0.037)	(0.108)	(0.094)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.181			0.233	0.122	0.830	
(0.057)			(0.070)	(0.023)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.US]-L2	-4776.09	0.070	0.347	400	1.364
		(0.033)	(0.080)	-	(0.021)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.071	0.134	0.087	2.428	0.178	0.431	0.307
(0.153)	(0.036)	(0.032)	(1.016)	(0.037)	(0.108)	(0.094)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.181			0.232	0.122	0.830	
(0.057)			(0.070)	(0.023)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.US]-L2	-4776.91	0.068	0.352	400	1.854
		(0.032)	(0.079)	-	(0.021)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.063	0.132	0.087	2.677	0.182	0.428	0.294
(0.151)	(0.034)	(0.031)	(1.075)	(0.039)	(0.029)	(0.037)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.183			0.234	0.125	0.827	
(0.057)			(0.030)	(0.013)	(0.006)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.HK-L2	-4777.26	0.158	-0.057	400	1.787
		(0.036)	(0.069)	-	(0.023)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.069	0.132	0.085	2.622	0.179	0.432	0.295
(0.153)	(0.034)	(0.032)	(0.966)	(0.037)	(0.123)	(0.105)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.183			0.233	0.124	0.828	
(0.057)			(0.071)	(0.024)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.HK-L2	-4776.67	0.157	-0.085	400	0.598
		(0.034)	(0.074)	-	(0.011)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.069	0.132	0.085	2.622	0.179	0.432	0.295
(0.153)	(0.034)	(0.032)	(0.966)	(0.037)	(0.123)	(0.105)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.183			0.233	0.124	0.828	
(0.057)			(0.071)	(0.024)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.HK-L2	-4776.67	0.157	-0.085	400	0.598
		(0.034)	(0.074)	-	(0.011)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.052	0.129	0.082	2.528	0.175	0.438	0.295
(0.152)	(0.035)	(0.033)	(0.992)	(0.036)	(0.112)	(0.103)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.191			0.240	0.125	0.826	
(0.058)			(0.074)	(0.024)	(0.034)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.HK]-L1	-4778.13	0.083	0.321	400	1.515
		(0.032)	(0.082)	-	(0.013)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.057	0.132	0.082	2.635	0.178	0.428	0.298
(0.152)	(0.035)	(0.033)	(1.013)	(0.038)	(0.115)	(0.104)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.187			0.237	0.123	0.829	
(0.058)			(0.071)	(0.023)	(0.032)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Jap]-L1	-4778.13	0.035	0.191	400	0.554
		(0.043)	(0.045)	-	(0.010)

Shgh-B – CAC

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.038	0.130	0.092	2.489	0.179	0.416	0.315
(0.146)	(0.035)	(0.031)	(1.031)	(0.038)	(0.116)	(0.101)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.161	-0.066		0.464	0.149	0.797	
(0.077)	(0.032)		(0.146)	(0.027)	(0.036)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
Time	-5002.59	0.010	0.252	400	0.734
		(0.039)	(0.052)	-	(0.008)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.049	0.126	0.095	2.557	0.176	0.427	0.304
(0.153)	(0.038)	(0.035)	(0.016)	(0.011)	(0.008)	(0.007)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.174	-0.061		0.468	0.152	0.794	
(0.076)	(0.002)		(0.047)	(0.010)	(0.007)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Fr]-L2	-5002.05	0.033	0.338	400	3.673
		(0.037)	(0.075)	-	(0.018)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.018	0.120	0.092	2.646	0.177	0.427	0.302
(0.126)	(0.033)	(0.029)	(0.104)	(0.002)	(0.010)	(0.011)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.174	-0.069		0.469	0.151	0.794	
(0.065)	(0.002)		(0.033)	(0.008)	(0.008)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Fr]-L2	-5002.17	0.033	0.350	400	1.395
		(0.001)	(0.069)	-	(0.029)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.036	0.142	0.092	2.397	0.175	0.441	0.312
(0.158)	(0.039)	(0.032)	(0.118)	(0.032)	(0.038)	(0.021)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.189	-0.063		0.469	0.155	0.791	
(0.077)	(0.031)		(0.149)	(0.029)	(0.037)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Fr]-L1	-5004.87	0.039	0.211	400	9.554
		(0.036)	(0.062)	-	(2.33)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.066	0.129	0.088	2.366	0.171	0.428	0.314
(0.147)	(0.037)	(0.034)	(0.950)	(0.037)	(0.116)	(0.103)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.172	-0.065		0.467	0.154	0.792	
(0.075)	(0.032)		(0.146)	(0.028)	(0.036)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.US-L2	-5002.33	0.400	0.045	400	-1.314
		(0.078)	(0.035)	-	(0.19)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.043	0.135	0.088	2.467	0.173	0.435	0.302
(0.148)	(0.037)	(0.033)	(0.935)	(0.037)	(0.113)	(0.101)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.183	-0.066		0.463	0.151	0.795	
(0.076)	(0.032)		(0.149)	(0.027)	(0.037)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.US]-L2	-5006.76	0.037	0.160	400	1.716
		(0.041)	(0.049)	-	(0.025)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.049	0.133	0.085	2.471	0.173	0.431	0.301
(0.141)	(0.037)	(0.033)	(0.935)	(0.037)	(0.115)	(0.10)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.182	-0.066		0.461	0.153	0.796	
(0.076)	(0.032)		(0.148)	(0.027)	(0.035)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.US]-L2	-5006.16	0.035	0.163	400	2.925
		(0.041)	(0.045)	-	(0.095)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.049	0.133	0.085	2.471	0.173	0.431	0.301
(0.141)	(0.037)	(0.033)	(0.935)	(0.037)	(0.115)	(0.10)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.182	-0.066		0.461	0.153	0.796	
(0.076)	(0.032)		(0.148)	(0.027)	(0.035)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.US]-L2	-5006.16	0.035	0.163	400	2.925
		(0.041)	(0.045)	-	(0.095)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.051	0.132	0.088	2.541	0.175	0.429	0.305
(0.152)	(0.035)	(0.033)	(0.995)	(0.037)	(0.115)	(0.10)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.181	-0.068		0.461	0.155	0.792	
(0.078)	(0.033)		(0.148)	(0.027)	(0.035)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.US]-L2	-5002.18	0.035	0.368	400	1.745
		(0.038)	(0.069)	-	(0.009)

Shgh-B – Nikkei

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.077	0.130	0.081	2.458	0.179	0.430	0.302
(0.145)	(0.035)	(0.034)	(0.928)	(0.036)	(0.034)	(0.027)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.055			0.374	0.128	0.832	
(0.082)			(0.166)	(0.027)	(0.039)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.US-L2	-5054.49	0.318	0.035	400	-2.524
		(0.086)	(0.036)	-	(0.082)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.038	0.132	0.092	2.497	0.175	0.435	0.301
(0.154)	(0.037)	(0.034)	(0.988)	(0.038)	(0.037)	(0.026)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.064			0.371	0.127	0.833	
(0.083)			(0.171)	(0.028)	(0.039)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.US]-L1	-5055.69	0.321	0.044	400	0.059
		(0.096)	(0.035)	-	(0.007)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.039	0.130	0.089	2.495	0.173	0.437	0.302
(0.154)	(0.037)	(0.031)	(0.988)	(0.037)	(0.035)	(0.026)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.064			0.371	0.127	0.833	
(0.081)			(0.171)	(0.028)	(0.039)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.US]-L1	-5055.02	0.323	0.041	400	0.003
		(0.091)	(0.037)	-	(0.009)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.071	0.136	0.089	2.491	0.177	0.431	0.309
(0.159)	(0.039)	(0.034)	(1.015)	(0.039)	(0.031)	(0.025)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.064			0.378	0.127	0.833	
(0.083)			(0.098)	(0.028)	(0.039)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.HK-L2	-5055.71	0.212	0.014	400	-2.299
		(0.062)	(0.039)	-	(0.029)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.061	0.130	0.085	2.577	0.177	0.431	0.298
(0.153)	(0.035)	(0.032)	(1.014)	(0.037)	(0.104)	(0.096)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.063			0.375	0.126	0.834	
(0.082)			(0.176)	(0.028)	(0.041)	

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.HK-L2	-5055.45	0.210	0.020	400	-0.724
		(0.059)	(0.037)	-	(0.010)

D.2. Estimation Results of STCC Models not reported in Chapter 4

ISX100 – DAX

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.565	0.037	0.288	0.067	0.925
(0.129)	(0.028)	(0.044)	(0.003)	(0.002)
μ_{20}		α_{20}	α_{21}	β_{21}
0.220		0.582	0.198	0.760
(0.052)		(0.052)	(0.010)	(0.008)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.Tr-L2	-3950.28	0.673	0.352	99	-6.52
		(0.049)	(0.028)	(0.71)	(0.147)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.536	0.039	0.243	0.060	0.933
(0.002)	(0.001)	(0.040)	(0.003)	(0.002)
μ_{20}		α_{20}	α_{21}	β_{21}
0.237		0.534	0.174	0.781
(0.003)		(0.015)	(0.004)	(0.004)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.Tr-L2	-3949.19	0.695	0.350	400	-1.242
		(0.043)	(0.022)	-	(0.047)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.523	0.045	0.533	0.070	0.914
(0.102)	(0.000)	(0.162)	(0.016)	(0.015)
μ_{20}		α_{20}	α_{21}	β_{21}
0.239		0.703	0.194	0.751
(0.007)		(0.091)	(0.016)	(0.022)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Tr]-L4	-3952.59	0.489	0.274	400	3.78
		(0.029)	(0.016)	-	(0.003)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.522	0.056	0.258	0.055	0.937
(0.107)	(0.001)	(0.058)	(0.015)	(0.013)
μ_{20}		α_{20}	α_{21}	β_{21}
0.245		0.589	0.182	0.773
(0.005)		(0.108)	(0.024)	(0.021)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Tr]-L4	-3952.15	0.490	0.285	400	13.34
		(0.025)	(0.024)	-	-

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.598	0.055	0.448	0.081	0.908
(0.105)	(0.002)	(0.033)	(0.009)	(0.006)
μ_{20}		α_{20}	α_{21}	β_{21}
0.253		0.581	0.201	0.758
(0.061)		(0.028)	(0.006)	(0.002)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Tr]-L4	-3951.99	0.552	0.320	400	0.325
		(0.036)	(0.021)	-	(0.007)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.587	0.057	0.507	0.089	0.899
(0.150)	(0.030)	(0.078)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.205		0.646	0.197	0.758
(0.022)		(0.063)	(0.008)	(0.006)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Tr]-L4	-3951.99	0.559	0.325	400	0.111
		(0.046)	(0.032)	-	(0.010)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.579	0.049	0.587	0.084	0.901
(0.140)	(0.028)	(0.009)	(0.013)	(0.011)
μ_{20}		α_{20}	α_{21}	β_{21}
0.228		0.669	0.193	0.755
(0.077)		(0.079)	(0.007)	(0.015)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Ger]-L3	-3954.47	0.445	0.248	400	3.31
		(0.027)	(0.051)	-	(0.028)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.558	0.051	0.383	0.072	0.918
(0.150)	(0.033)	(0.324)	(0.027)	(0.032)
μ_{20}		α_{20}	α_{21}	β_{21}
0.223		0.648	0.192	0.758
(0.086)		(0.204)	(0.037)	(0.043)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Ger]-L3	-3954.35	0.444	0.257	400	10
		(0.032)	(0.059)	-	-

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.578	0.050	0.456	0.089	0.900
(0.115)	(0.027)	(0.014)	(0.003)	(0.000)
μ_{20}		α_{20}	α_{21}	β_{21}
0.222		0.637	0.194	0.757
(0.061)		(0.056)	(0.009)	(0.008)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Ger]-L3	-3956.67	0.409	0.259	400	1.425
		(0.003)	(0.049)	-	(0.017)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.532	0.054	0.263	0.062	0.931
(0.181)	(0.033)	(0.267)	(0.026)	(0.031)
μ_{20}		α_{20}	α_{21}	β_{21}
0.228		0.609	0.189	0.764
(0.098)		(0.187)	(0.036)	(0.041)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Fr]-L3	-3957.16	0.429	0.347	400	5.151
		(0.037)	(0.043)	-	(0.17)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.557	0.046	0.257	0.067	0.927
(0.174)	(0.034)	(0.236)	(0.024)	(0.027)
μ_{20}		α_{20}	α_{21}	β_{21}
0.236		0.578	0.196	0.764
(0.094)		(0.175)	(0.037)	(0.040)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.UK]-L2	-3954.71	0.342	0.505	400	1.924
		(0.034)	(0.042)	-	(0.031)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.537	0.058	0.346	0.073	0.918
(0.179)	(0.033)	(0.266)	(0.025)	(0.028)
μ_{20}		α_{20}	α_{21}	β_{21}
0.231		0.512	0.181	0.783
(0.097)		(0.169)	(0.036)	(0.039)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vol.UK-L3	-3953.83	0.374	0.716	400	14.9
		(0.032)	(0.065)	-	-

ISX100 – CAC

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.586	0.033	0.479	0.094	0.896
(0.138)	(0.005)	(0.069)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.181		0.459	0.182	0.772
(0.015)		(0.027)	(0.002)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.Tr-L2	-3892.25	0.772	0.353	400	-1.601
		(0.050)	(0.022)	-	(0.019)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.562	0.051	0.461	0.073	0.915
(0.147)	(0.000)	(0.062)	(0.008)	(0.007)
μ_{20}		α_{20}	α_{21}	β_{21}
0.181		0.543	0.177	0.772
(0.002)		(0.086)	(0.007)	(0.019)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Tr]-L4	-3890.05	0.517	0.238	400	3.806
		(0.022)	(0.041)	-	(0.003)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.506	0.055	0.217	0.055	0.939
(0.132)	(0.000)	(0.201)	(0.017)	(0.019)
μ_{20}		α_{20}	α_{21}	β_{21}
0.171		0.344	0.142	0.825
(0.008)		(0.147)	(0.025)	(0.033)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Tr]-L4	-3889.34	0.518	0.239	36	14.31
		(0.038)	(0.051)	(25)	(0.092)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.604	0.056	0.476	0.092	0.896
(0.113)	(0.000)	(0.063)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.198		0.415	0.176	0.789
(0.002)		(0.010)	(0.009)	(0.006)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Tr]-L4	-3891.87	0.550	0.297	400	0.339
		(0.036)	(0.025)	-	(0.015)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.593	0.054	0.516	0.094	0.897
(0.116)	(0.000)	(0.040)	(0.003)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.154		0.435	0.181	0.785
(0.002)		(0.052)	(0.007)	(0.006)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Tr]-L4	-3892.23	0.554	0.310	400	0.109
		(0.024)	(0.01)	-	(0.003)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.543	0.041	0.271	0.073	0.921
(0.161)	(0.034)	(0.253)	(0.026)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.180		0.388	0.158	0.806
(0.081)		(0.139)	(0.034)	(0.04)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Fr]-L3	-3896.21	0.399	-0.125	400	10.13
		(0.029)	(0.205)	-	(0.375)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.545	0.040	0.275	0.073	0.921
(0.182)	(0.033)	(0.255)	(0.026)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.181		0.389	0.158	0.804
(0.090)		(0.138)	(0.032)	(0.04)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Fr]-L3	-3896.70	0.398	-0.081	400	85
		(0.031)	(0.196)	-	-

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.559	0.042	0.368	0.081	0.911
(0.178)	(0.034)	(0.284)	(0.025)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.177		0.423	0.163	0.797
(0.086)		(0.144)	(0.033)	(0.04)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Ger]-L3	-3896.88	0.432	0.269	400	3.269
		(0.035)	(0.059)	-	(0.037)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.559	0.042	0.365	0.081	0.911
(0.175)	(0.033)	(0.283)	(0.024)	(0.028)
μ_{20}		α_{20}	α_{21}	β_{21}
0.176		0.423	0.163	0.797
(0.089)		(0.149)	(0.035)	(0.042)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Ger]-L3	-3896.86	0.433	0.269	400	10.58
		(0.033)	(0.059)	-	(0.103)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.563	0.051	0.408	0.077	0.913
(0.148)	(0.032)	(0.287)	(0.025)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.193		0.460	0.156	0.798
(0.075)		(0.157)	(0.034)	(0.042)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vol.Ger-L2	-3894.69	0.508	0.308	400	7.46
		(0.038)	(0.034)	-	(0.171)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.567	0.034	0.303	0.082	0.913
(0.169)	(0.034)	(0.240)	(0.023)	(0.025)
μ_{20}		α_{20}	α_{21}	β_{21}
0.193		0.403	0.179	0.787
(0.086)		(0.141)	(0.035)	(0.041)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.UK]-L2	-3892.31	0.326	0.591	400	2.545
		(0.033)	(0.046)	-	(0.037)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.591	0.035	0.281	0.077	0.918
(0.169)	(0.034)	(0.249)	(0.024)	(0.026)
μ_{20}		α_{20}	α_{21}	β_{21}
0.184		0.406	0.171	0.792
(0.087)		(0.147)	(0.032)	(0.041)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.UK]-L2	-3893.78	0.33	0.559	400	1.063
		(0.037)	(0.048)	-	(0.014)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.579	0.046	0.312	0.081	0.914
(0.168)	(0.033)	(0.259)	(0.026)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.177		0.368	0.164	0.804
(0.083)		(0.131)	(0.033)	(0.038)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vol.UK-L4	-3895.81	0.369	0.718	400	14.87
		(0.03)	(0.068)	-	-

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.539	0.048	0.316	0.074	0.919
(0.155)	(0.033)	(0.265)	(0.025)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.180		0.409	0.161	0.80
(0.078)		(0.144)	(0.035)	(0.041)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.US]-L3	-3897.01	0.437	0.285	400	4.657
		(0.035)	(0.049)	-	(0.025)

ISX100 – FTSE

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.567	0.043	0.481	0.094	0.896
(0.156)	(0.005)	(0.098)	(0.004)	(0.004)
μ_{20}		α_{20}	α_{21}	β_{21}
0.187		0.364	0.143	0.793
(0.057)		(0.028)	(0.018)	(0.011)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Tr]-L4	-3718.76	0.446	0.128	400	9.99
		(0.024)	(0.106)	-	(0.58)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.511	0.046	0.121	0.056	0.941
(0.169)	(0.033)	(0.167)	(0.020)	(0.021)
μ_{20}		α_{20}	α_{21}	β_{21}
0.157		0.270	0.110	0.840
(0.072)		(0.088)	(0.025)	(0.036)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Tr]-L4	-3717.15	0.458	0.137	400	99
		(0.031)	(0.099)	-	-

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.541	0.046	0.498	0.094	0.895
(0.162)	(0.000)	(0.077)	(0.004)	(0.004)
μ_{20}		α_{20}	α_{21}	β_{21}
0.182		0.356	0.149	0.788
(0.001)		(0.013)	(0.002)	(0.006)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Tr]-L4	-3717.78	0.446	0.161	400	1.342
		(0.042)	(0.106)	-	(0.056)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.528	0.041	0.386	0.092	0.902
(0.194)	(0.027)	(0.026)	(0.004)	(0.004)
μ_{20}		α_{20}	α_{21}	β_{21}
0.202		0.374	0.142	0.793
(0.012)		(0.013)	(0.006)	(0.005)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Tr]-L4	-3717.56	0.464	0.161	400	1.718
		(0.029)	(0.07)	-	(0.081)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.528	0.053	0.571	0.087	0.899
(0.194)	(0.021)	(0.071)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.179		0.376	0.143	0.791
(0.002)		(0.008)	(0.002)	(0.002)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vol.Tr-L2	-3710.04	0.597	0.300	400	23.5
		(0.033)	(0.031)	-	(0.903)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.595	0.049	0.483	0.095	0.895
(0.150)	(0.032)	(0.071)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.184		0.302	0.138	0.812
(0.066)		(0.022)	(0.009)	(0.006)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.UK]-L2	-3716.64	0.347	0.563	400	1.93
		(0.031)	(0.039)	-	(0.185)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.612	0.050	0.504	0.098	0.893
(0.150)	(0.032)	(0.072)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.171		0.333	0.139	0.806
(0.065)		(0.024)	(0.009)	(0.007)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.UK]-L2	-3717.76	0.332	0.536	24	0.695
		(0.029)	(0.036)	(32)	(0.063)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.518	0.051	0.258	0.074	0.921
(0.151)	(0.032)	(0.242)	(0.026)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.155		0.295	0.121	0.826
(0.068)		(0.089)	(0.025)	(0.035)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Ger]-L3	-3720.48	0.455	0.323	400	3.273
		(0.031)	(0.058)	-	(0.025)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.518	0.051	0.259	0.074	0.921
(0.180)	(0.032)	(0.265)	(0.027)	(0.031)
μ_{20}		α_{20}	α_{21}	β_{21}
0.155		0.295	0.121	0.826
(0.074)		(0.089)	(0.025)	(0.035)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Ger]-L3	-3720.46	0.455	0.323	400	10.73
		(0.032)	(0.059)	-	(3.55)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.508	0.052	0.231	0.072	0.924
(0.147)	(0.032)	(0.232)	(0.025)	(0.028)
μ_{20}		α_{20}	α_{21}	β_{21}
0.157		0.291	0.120	0.827
(0.065)		(0.090)	(0.025)	(0.035)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Fr]-L3	-3721.36	0.443	0.339	400	11.57
		(0.028)	(0.062)	-	(90)

ISX100 – S&P500

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.539	0.054	0.417	0.085	0.906
(0.205)	(0.002)	(0.069)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.144		0.067	0.079	0.912
(0.031)		(0.014)	(0.004)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Tr]-L3	-3751.92	0.503	0.327	400	4.113
		(0.058)	(0.029)	-	(0.195)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.556	0.067	0.539	0.088	0.899
(0.136)	(0.000)	(0.217)	(0.013)	(0.017)
μ_{20}		α_{20}	α_{21}	β_{21}
0.132		0.084	0.082	0.906
(0.000)		(0.033)	(0.018)	(0.016)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Tr]-L4	-3748.64	0.509	0.281	400	2.619
		(0.036)	(0.034)	-	(0.008)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.512	0.058	0.504	0.094	0.895
(0.141)	(0.029)	(0.073)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.189		0.098	0.086	0.898
(0.048)		(0.014)	(0.004)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Tr]-L4	-3749.58	0.425	0.146	400	1.232
		(0.022)	(0.048)	-	(0.039)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.559	0.061	0.237	0.069	0.926
(0.182)	(0.033)	(0.305)	(0.032)	(0.036)
μ_{20}		α_{20}	α_{21}	β_{21}
0.134		0.065	0.078	0.913
(0.073)		(0.039)	(0.017)	(0.019)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Ger]-L3	-3748.13	0.457	0.212	400	3.177
		(0.034)	(0.059)	-	(0.022)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.550	0.059	0.193	0.064	0.932
(0.179)	(0.033)	(0.256)	(0.028)	(0.031)
μ_{20}		α_{20}	α_{21}	β_{21}
0.133		0.058	0.077	0.916
(0.072)		(0.038)	(0.017)	(0.020)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Ger]-L3	-3749.83	0.434	0.199	400	1.167
		(0.028)	(0.070)	-	(0.010)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.557	0.061	0.238	0.069	0.926
(0.188)	(0.033)	(0.297)	(0.031)	(0.035)
μ_{20}		α_{20}	α_{21}	β_{21}
0.134		0.065	0.078	0.913
(0.075)		(0.039)	(0.018)	(0.021)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Ger]-L3	-3747.97	0.458	0.209	400	10.12
		(0.034)	(0.061)	-	(0.010)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.548	0.061	0.207	0.066	0.929
(0.190)	(0.034)	(0.257)	(0.028)	(0.032)
μ_{20}		α_{20}	α_{21}	β_{21}
0.132		0.058	0.077	0.916
(0.076)		(0.037)	(0.017)	(0.019)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Ger]-L3	-3749.60	0.433	0.184	400	1.548
		(0.033)	(0.076)	-	(0.019)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.510	0.065	0.216	0.064	0.931
(0.187)	(0.033)	(0.264)	(0.027)	(0.031)
μ_{20}		α_{20}	α_{21}	β_{21}
0.138		0.055	0.075	0.919
(0.076)		(0.035)	(0.017)	(0.019)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.Fr]-L3	-3750.22	0.480	0.296	400	1.854
		(0.034)	(0.044)	-	(0.016)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.516	0.063	0.229	0.067	0.928
(0.187)	(0.032)	(0.259)	(0.027)	(0.030)
μ_{20}		α_{20}	α_{21}	β_{21}
0.130		0.054	0.075	0.919
(0.075)		(0.032)	(0.015)	(0.017)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.Fr]-L3	-3749.76	0.481	0.288	400	0.722
		(0.037)	(0.043)	-	(0.009)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.518	0.064	0.188	0.062	0.933
(0.167)	(0.032)	(0.241)	(0.026)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.131		0.054	0.073	0.921
(0.070)		(0.034)	(0.016)	(0.018)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.Fr]-L3	-3750.15	0.469	0.284	400	5.05
		(0.035)	(0.047)	-	(1.97)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.516	0.063	0.229	0.067	0.929
(0.183)	(0.032)	(0.291)	(0.031)	(0.035)
μ_{20}		α_{20}	α_{21}	β_{21}
0.130		0.054	0.075	0.919
(0.074)		(0.033)	(0.015)	(0.017)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.Fr]-L3	-3749.72	0.482	0.288	400	0.521
		(0.033)	(0.044)	-	(0.016)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.518	0.061	0.141	0.058	0.939
(0.185)	(0.032)	(0.189)	(0.023)	(0.025)
μ_{20}		α_{20}	α_{21}	β_{21}
0.143		0.055	0.074	0.919
(0.075)		(0.036)	(0.016)	(0.019)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.UK]-L3	-3751.57	0.435	0.265	400	2.179
		(0.036)	(0.059)	-	(0.009)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.513	0.065	0.129	0.058	0.939
(0.174)	(0.032)	(0.161)	(0.018)	(0.020)
μ_{20}		α_{20}	α_{21}	β_{21}
0.140		0.056	0.074	0.919
(0.073)		(0.036)	(0.016)	(0.018)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.UK]-L3	-3749.51	0.448	0.230	400	1.159
		(0.036)	(0.061)	-	(0.012)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.513	0.060	0.142	0.059	0.938
(0.186)	(0.033)	(0.200)	(0.022)	(0.025)
μ_{20}		α_{20}	α_{21}	β_{21}
0.141		0.054	0.074	0.919
(0.074)		(0.036)	(0.016)	(0.018)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.UK]-L3	-3751.44	0.433	0.257	400	5.829
		(0.035)	(0.056)	-	(0.014)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.514	0.065	0.128	0.058	0.939
(0.157)	(0.034)	(0.202)	(0.023)	(0.026)
μ_{20}		α_{20}	α_{21}	β_{21}
0.140		0.056	0.074	0.919
(0.071)		(0.036)	(0.017)	(0.020)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.UK]-L3	-3749.45	0.449	0.229	400	1.341
		(0.035)	(0.051)	-	(0.026)

D.3. Estimation Results of STCC Models not reported in Chapter 5

S&P-AG – S&P500

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.065	0.084	0.051	0.935
(0.067)	(0.011)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.180	0.071	0.076	0.909
(0.052)	(0.006)	(0.001)	(0.001)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vol.AG-L4	-4712.19	-0.037	0.223	400	5.699
		(0.037)	(0.039)	-	(0.152)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.058	0.099	0.052	0.931
(0.066)	(0.068)	(0.019)	(0.029)
μ_{20}	α_{20}	α_{21}	β_{21}
0.183	0.078	0.083	0.902
(0.053)	(0.038)	(0.019)	(0.024)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vix-L2	-4711.79	0.007	0.345	400	27.89
		(0.033)	(0.065)	-	(0.234)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.053	0.082	0.052	0.935
(0.066)	(0.011)	(0.002)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.179	0.069	0.078	0.909
(0.053)	(0.009)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
vol.SP-L2	-4709.99	0.034	0.578	400	10
		(0.003)	(0.068)	-	(0.4)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.065	0.085	0.049	0.938
(0.067)	(0.046)	(0.003)	(0.012)
μ_{20}	α_{20}	α_{21}	β_{21}
0.172	0.068	0.074	0.911
(0.054)	(0.031)	(0.018)	(0.022)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.SP]-L4	-4715.49	0.032	0.353	400	15
		(0.030)	(0.081)	-	(0.6)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.060	0.084	0.051	0.935
(0.067)	(0.011)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.178	0.070	0.077	0.909
(0.053)	(0.009)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.AG]-L2	-4716.97	0.090	-0.531	1.1	4.95
		(0.029)	(0.193)	(0.79)	(1.22)

S&P-PM – S&P500

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.001	0.082	0.099	0.884
(0.047)	(0.025)	(0.016)	(0.017)
μ_{20}	α_{20}	α_{21}	β_{21}
0.179	0.075	0.077	0.908
(0.007)	(0.020)	(0.013)	(0.013)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.PM-L2	-4529.00	-0.069	0.193	400	1.5
		(0.032)	(0.051)	-	(0.026)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.006	0.086	0.10	0.883
(0.051)	(0.010)	(0.004)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.171	0.069	0.077	0.909
(0.047)	(0.009)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.PM-L2	-4531.58	-0.073	0.121	400	0.485
		(0.036)	(0.048)	-	(0.037)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.002	0.089	0.10	0.882
(0.045)	(0.004)	(0.004)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.189	0.070	0.077	0.909
(0.002)	(0.008)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[err.PM]-L2	-4530.88	-0.129	0.076	400	0.99
		(0.040)	(0.028)	-	(0.014)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.002	0.086	0.10	0.882
(0.050)	(0.010)	(0.004)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.183	0.070	0.077	0.909
(0.051)	(0.009)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[err.PM]-L2	-4530.81	-0.124	0.080	400	1
		(0.046)	(0.035)	-	(0.54)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.003	0.083	0.103	0.882
(0.043)	(0.001)	(0.005)	(0.005)
μ_{20}	α_{20}	α_{21}	β_{21}
0.174	0.069	0.076	0.911
(0.043)	(0.011)	(0.008)	(0.007)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
err.SP-L1	-4532.59	-0.121	0.056	400	-1.36
		(0.036)	(0.029)	-	(0.14)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.004	0.084	0.101	0.882
(0.050)	(0.001)	(0.001)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.172	0.069	0.077	0.909
(0.053)	(0.009)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
serr.SP-L1	-4532.79	-0.117	0.056	400	-0.587
		(0.007)	(0.034)	-	(0.028)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.003	0.084	0.102	0.883
(0.047)	(0.009)	(0.002)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.172	0.069	0.077	0.909
(0.049)	(0.008)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
A[serr.SP]-L1	-4533.31	0.025	-0.216	400	1.49
		(0.019)	(0.084)	-	(0.203)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.003	0.084	0.101	0.883
(0.046)	(0.008)	(0.004)	(0.003)
μ_{20}	α_{20}	α_{21}	β_{21}
0.173	0.069	0.077	0.909
(0.048)	(0.008)	(0.003)	(0.003)

Correlation Eq.

Transition Variable	ML Value	ρ_1	ρ_2	γ	c
S[serr.SP]-L1	-4533.29	0.024	-0.216	400	2.21
		(0.027)	(0.081)	-	(1.41)

APPENDIX E
DSTCC-GARCH MODEL ESTIMATES NOT REPORTED IN CHAPTERS

E.1. Estimation Results of DSTCC Models not reported in Chapter 3

Shgh-A – S&P500

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.170	0.083	0.113	0.765	0.171	0.806
	(0.094)	(0.002)	(0.003)	(0.092)	(0.009)	(0.010)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.158			0.08	0.08	0.908
	(0.008)			(0.011)	(0.005)	(0.005)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Ch]-L2	0.123	-0.089	0.464	0.196	19	108	0.669	0.872
ML: -4932.66	(0.060)	(0.035)	(0.064)	(0.031)	(11)	(13)	(0.048)	(0.021)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.157	0.092	0.135	0.841	0.174	0.799
	(0.084)	(0.001)	(0.003)	(0.099)	(0.017)	(0.012)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.203			0.07	0.08	0.908
	(0.003)			(0.001)	(0.004)	(0.005)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.Ch]-L2	0.064	-0.181	0.312	0.094	52	9	0.637	0.625
ML: -4931.21	(0.048)	(0.056)	(0.026)	(0.003)	(2.5)	(0.45)	(0.04)	(0.1)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.171	0.097	0.112	0.818	0.170	0.804
	(0.103)	(0.031)	(0.032)	(0.293)	(0.027)	(0.036)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.168			0.08	0.08	0.909
	(0.053)			(0.001)	(0.003)	(0.005)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.US-L1	0.064	-0.181	0.312	0.094	52	9	0.637	0.625
ML: -4930.73	(0.048)	(0.056)	(0.026)	(0.003)	(2.5)	(0.45)	(0.04)	(0.1)

Shgh-A – FTSE

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.211	0.098	0.119	0.876	0.173	0.797
	(0.114)	(0.031)	(0.032)	(0.258)	(0.029)	(0.032)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.219			0.273	0.131	0.813
	(0.055)			(0.069)	(0.023)	(0.031)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.Jap]-L2	-0.036	0.557	0.191	-0.094	145	400	0.521	7.9
ML: -4935.37	(0.048)	(0.167)	(0.043)	(0.037)	(212)	-	(0.02)	-

Shgh-A – CAC

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.179	0.089	0.131	0.867	0.174	0.799
	(0.103)	(0.03)	(0.031)	(0.082)	(0.008)	(0.006)
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}
	0.177	-0.072		0.518	0.162	0.775
	(0.066)	(0.031)		(0.044)	(0.010)	(0.008)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Ch]-L2	0.035	-0.091	0.403	0.107	36	400	0.705	4.91
ML: -5165.54	(0.047)	(0.072)	(0.05)	(0.083)	(34)	-	(0.04)	(0.52)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.181	0.083	0.125	0.843	0.170	0.802
	(0.111)	(0.031)	(0.032)	(0.141)	(0.014)	(0.006)
(2)	μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}
	0.177	-0.069		0.514	0.158	0.778
	(0.074)	(0.03)		(0.143)	(0.028)	(0.037)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + VIX-L3	0.018	-0.102	0.555	0.129	12	400	0.809	26
ML: -5165.82	(0.044)	(0.094)	(0.197)	(0.192)	(8)	-	(0.09)	(0.3)

Shgh-A – Nikkei

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.174	0.093	0.116	0.861	0.179	0.795
	(0.105)	(0.031)	(0.032)	(0.247)	(0.03)	(0.031)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.026			0.439	0.135	0.817
	(0.08)			(0.182)	(0.026)	(0.04)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.HK-L2	0.081	-0.074	0.434	0.139	400	400	0.833	1.44
ML: -5229.87	(0.039)	(0.072)	(0.078)	(0.118)	-	-	(0.005)	(0.21)

	Mean Eq			Volatility Eq		
(1)	μ_{10}	μ_{11}	μ_{13}	α_{10}	α_{11}	β_{11}
	0.162	0.094	0.117	0.875	0.175	0.797
	(0.105)	(0.032)	(0.032)	(0.244)	(0.029)	(0.031)
(2)	μ_{20}			α_{20}	α_{21}	β_{21}
	0.034			0.431	0.134	0.819
	(0.081)			(0.177)	(0.026)	(0.039)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.HK]-L3	0.053	-0.065	0.401	0.024	400	3.4	0.834	35
ML: -5231.35	(0.036)	(0.142)	(0.067)	(0.156)	-	(12)	(0.005)	(1.56)

Shgh-B – S&P500

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.008	0.125	0.088	2.471	0.181	0.402	0.329
(0.151)	(0.035)	(0.032)	(0.959)	(0.036)	(0.119)	(0.117)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.161			0.066	0.083	0.906	
(0.056)			(0.031)	(0.017)	(0.020)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.Jap]-L3	-0.027	-0.074	0.368	1	7.5	400	0.946	3.08
ML: -4768.44	(0.063)	(0.072)	(0.082)	-	(3.6)	-	(0.043)	(0.016)

Shgh-B – FTSE

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.074	0.130	0.087	2.620	0.173	0.431	0.299
(0.135)	(0.033)	(0.029)	(0.018)	(0.010)	(0.007)	(0.008)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.179			0.239	0.129	0.823	
(0.055)			(0.011)	(0.011)	(0.007)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2 + err.HK-L2	0.066	-0.247	0.296	0.151	400	400	1.344	1.787
ML: -4768.01	(0.045)	(0.076)	(0.038)	(0.099)	-	-	(0.015)	(0.017)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.061	0.131	0.087	2.545	0.175	0.431	0.303
(0.147)	(0.033)	(0.028)	(0.175)	(0.010)	(0.008)	(0.007)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.179			0.240	0.127	0.828	
(0.055)			(0.018)	(0.006)	(0.005)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2 + S[err.Jap]-L3	0.121	-0.061	0.368	0.195	400	400	1.344	0.485
ML: -4770.57	(0.070)	(0.055)	(0.082)	(0.057)	-	-	(0.015)	(0.047)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.024	0.118	0.080	2.907	0.173	0.419	0.300
(0.142)	(0.031)	(0.030)	(0.226)	(0.011)	(0.015)	(0.008)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.178			0.226	0.126	0.829	
(0.024)			(0.023)	(0.010)	(0.006)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[err.UK]-L2 + vol.Jap-L2	0.038	-0.630	0.301	0.072	6.83	30.54	1.429	15
ML: -4766.34	(0.040)	(0.128)	(0.049)	(0.095)	(5.95)	(22)	(0.074)	(0.23)

Shgh-B – CAC

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.046	0.127	0.090	2.516	0.172	0.432	0.304
(0.128)	(0.031)	(0.029)	(0.264)	(0.001)	(0.011)	(0.004)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.189	-0.066		0.474	0.157	0.788	
(0.054)	(0.001)		(0.018)	(0.008)	(0.010)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2 + A[err.Fr]-L1	-0.009	0.190	0.372	0.447	400	400	1.417	3.09
ML: -4998.35	(0.038)	(0.048)	(0.069)	(0.087)	-	-	(0.012)	(0.66)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.029	0.126	0.088	2.673	0.175	0.429	0.299
(0.151)	(0.039)	(0.041)	(0.218)	(0.011)	(0.009)	(0.004)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.196	-0.065		0.471	0.156	0.789	
(0.082)	(0.001)		(0.070)	(0.020)	(0.009)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2 + S[err.Fr]-L1	-0.002	0.219	0.341	0.596	400	400	1.417	13
ML: -4997.21	(0.041)	(0.079)	(0.083)	(0.110)	-	-	(0.012)	(0.04)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.038	0.135	0.079	2.695	0.171	0.426	0.304
(0.136)	(0.029)	(0.032)	(0.048)	(0.001)	(0.005)	(0.009)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.197	-0.062		0.501	0.167	0.777	
(0.061)	(0.006)		(0.054)	(0.012)	(0.013)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2 + S[serr.Fr]-L1	-0.012	0.130	0.287	0.670	400	400	1.323	1.078
ML: -4996.99	(0.001)	(0.059)	(0.082)	(0.076)	-	-	(0.006)	(0.018)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.071	0.125	0.081	2.801	0.180	0.411	0.301
(0.150)	(0.033)	(0.032)	(0.918)	(0.035)	(0.115)	(0.111)
μ_{20}	μ_{211}		α_{20}	α_{21}	β_{21}	
0.187	-0.072		0.465	0.154	0.791	
(0.075)	(0.030)		(0.151)	(0.028)	(0.037)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
A[serr.US]-L2 + S[err.Jap]-L3	0.059	-0.281	0.365	-0.656	400	400	1.323	16
ML: -4997.12	(0.033)	(0.109)	(0.077)	(0.176)	-	-	(0.006)	(0.078)

Shgh-B – Nikkei

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.105	0.133	0.085	2.486	0.179	0.433	0.298
(0.149)	(0.035)	(0.031)	(1.054)	(0.038)	(0.107)	(0.097)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.059			0.368	0.129	0.833	
(0.083)			(0.167)	(0.027)	(0.038)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
serr.US-L2 + err.US-L4	0.350	-0.665	0.039	-0.020	400	400	-1.277	2.51
ML: -5052.15	(0.085)	(0.250)	(0.038)	(0.122)	-	-	(0.039)	(0.05)

Mean Eq			Volatility Eq			
μ_{10}	μ_{11}	μ_{12}	α_{10}	α_{11}	β_{11}	β_{13}
0.048	0.125	0.089	2.501	0.177	0.429	0.303
(0.149)	(0.033)	(0.031)	(0.172)	(0.010)	(0.008)	(0.007)
μ_{20}			α_{20}	α_{21}	β_{21}	
0.062			0.369	0.124	0.835	
(0.081)			(0.039)	(0.006)	(0.006)	

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
serr.US-L2 + vol.Jap-L1	0.295	0.039	-0.883	-0.192	400	400	-0.192	17
ML: -5046.97	(0.084)	(0.038)	(0.06)	(0.134)	-	-	(0.134)	-

E.2. Estimation Results of DSTCC Models not reported in Chapter 4

ISX100 – DAX

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.512	0.052	0.496	0.066	0.919
(0.133)	(0.007)	(0.292)	(0.021)	(0.026)
μ_{20}		α_{20}	α_{21}	β_{21}
0.228		0.595	0.173	0.781
(0.016)		(0.155)	(0.024)	(0.029)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.Tr]-L2	0.187	0.539	0.652	0.741	400	400	0.685	73
ML: -3927.42	(0.045)	(0.062)	(0.029)	(0.105)	-	-	(0.004)	-

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.543	0.057	0.691	0.082	0.899
(0.159)	(0.038)	(0.158)	(0.006)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.243		0.645	0.187	0.768
(0.095)		(0.023)	(0.002)	(0.010)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + vol.Tr-L1	0.170	0.388	0.654	0.697	400	400	0.685	41
ML: -3931.37	(0.106)	(0.119)	(0.082)	(0.122)	-	-	(0.004)	-

ISX100 – CAC

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.672	0.043	0.522	0.073	0.912
(0.101)	(0.000)	(0.083)	(0.005)	(0.008)
μ_{20}		α_{20}	α_{21}	β_{21}
0.229		0.504	0.179	0.782
(0.002)		(0.002)	(0.001)	(0.000)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.Tr-L2	0.691	0.193	0.836	0.666	32	400	0.668	-1.48
ML: -3864.49	(0.047)	(0.023)	(0.070)	(0.047)	(20)	-	(0.024)	(0.014)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.602	0.067	0.541	0.076	0.908
(0.134)	(0.004)	(0.154)	(0.014)	(0.013)
μ_{20}		α_{20}	α_{21}	β_{21}
0.231		0.444	0.166	0.798
(0.006)		(0.115)	(0.021)	(0.027)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.Tr]-L2	0.138	0.634	0.679	0.723	28	5.09	0.660	81
ML: -3861.71	(0.026)	(0.043)	(0.035)	(0.105)	(15)	(2.15)	(0.028)	(2)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.581	0.032	0.581	0.085	0.899
(0.049)	(0.002)	(0.041)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.163		0.489	0.177	0.781
(0.002)		(0.001)	(0.006)	(0.004)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[serr.Tr]-L2	0.173	0.713	0.673	0.718	31	400	0.672	1.657
ML: -3862.35	(0.034)	(0.044)	(0.023)	(0.063)	(15)	-	(0.019)	(0.034)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.604	0.030	0.582	0.086	0.898
(0.123)	(0.009)	(0.066)	(0.004)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.181		0.484	0.183	0.778
(0.007)		(0.031)	(0.005)	(0.004)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.Tr]-L2	0.170	0.727	0.678	0.722	29	27.7	0.678	2.76
ML: -3862.31	(0.045)	(0.057)	(0.029)	(0.082)	(9.8)	(7.8)	(0.024)	(0.095)

ISX100 – FTSE

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.609	0.069	0.547	0.088	0.899
(0.156)	(0.032)	(0.072)	(0.005)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.284		0.354	0.147	0.800
(0.054)		(0.022)	(0.010)	(0.007)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.Tr]-L2	0.185	0.594	0.654	0.819	29	1.19	0.637	82
ML: -3694.66	(0.052)	(0.070)	(0.041)	(0.049)	(22)	(0.95)	(0.028)	(1.92)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.509	0.052	0.527	0.082	0.903
(0.113)	(0.003)	(0.038)	(0.008)	(0.007)
μ_{20}		α_{20}	α_{21}	β_{21}
0.156		0.369	0.148	0.793
(0.003)		(0.014)	(0.001)	(0.001)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.Tr]-L2	0.198	0.610	0.646	0.738	21	400	0.629	2.67
ML: -3695.71	(0.032)	(0.041)	(0.033)	(0.071)	(1.17)	-	(0.023)	(0.029)

ISX100 – S&P500

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.534	0.067	0.569	0.080	0.905
(0.135)	(0.032)	(0.259)	(0.021)	(0.024)
μ_{20}		α_{20}	α_{21}	β_{21}
0.146		0.089	0.077	0.910
(0.058)		(0.038)	(0.016)	(0.019)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.US]-L1	0.237	0.211	0.601	0.457	400	400	0.565	2.65
ML: -3738.82	(0.058)	(0.051)	(0.039)	(0.070)	-	-	(0.005)	(0.617)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.539	0.067	0.535	0.089	0.898
(0.129)	(0.029)	(0.004)	(0.000)	(0.003)
μ_{20}		α_{20}	α_{21}	β_{21}
0.142		0.089	0.082	0.906
(0.055)		(0.012)	(0.004)	(0.003)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.US]-L1	0.201	0.377	0.582	0.234	400	400	0.566	2.325
ML: -3736.87	(0.001)	(0.085)	(0.035)	(0.187)	-	-	(0.003)	(0.134)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.552	0.067	0.601	0.087	0.898
(0.180)	(0.034)	(0.329)	(0.025)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.150		0.087	0.081	0.906
(0.074)		(0.044)	(0.017)	(0.020)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.Ger-L4	-0.106	0.297	0.335	0.565	400	400	0.566	-4.161
ML: -3734.42	(0.10)	(0.048)	(0.221)	(0.036)	-	-	(0.005)	(3.22)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.555	0.063	0.619	0.089	0.896
(0.180)	(0.032)	(0.324)	(0.024)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.157		0.088	0.082	0.906
(0.074)		(0.043)	(0.018)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.Ger-L4	-0.143	0.304	0.365	0.562	400	400	0.566	-1.592
ML: -3734.59	(0.104)	(0.047)	(0.219)	(0.037)	-	-	(0.005)	(0.021)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.523	0.064	0.568	0.083	0.903
(0.146)	(0.032)	(0.370)	(0.027)	(0.032)
μ_{20}		α_{20}	α_{21}	β_{21}
0.144		0.089	0.082	0.906
(0.065)		(0.044)	(0.017)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.Ger]-L1	-0.115	0.272	0.677	0.513	400	400	0.566	0.505
ML: -3734.82	(0.136)	(0.045)	(0.052)	(0.046)	-	-	(0.005)	(0.022)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.578	0.067	0.666	0.088	0.896
(0.182)	(0.032)	(0.357)	(0.024)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.142		0.094	0.083	0.905
(0.075)		(0.043)	(0.018)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[serr.Ger]-L3	0.324	0.147	0.628	0.491	400	400	0.566	0.614
ML: -3736.78	(0.056)	(0.053)	(0.042)	(0.056)	-	-	(0.005)	(0.010)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.578	0.067	0.668	0.088	0.896
(0.179)	(0.033)	(0.394)	(0.027)	(0.033)
μ_{20}		α_{20}	α_{21}	β_{21}
0.142		0.094	0.083	0.904
(0.073)		(0.045)	(0.017)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.Ger]-L3	0.324	0.147	0.628	0.491	400	400	0.566	0.377
ML: -3736.74	(0.058)	(0.054)	(0.047)	(0.054)	-	-	(0.005)	(0.010)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.552	0.062	0.627	0.085	0.899
(0.182)	(0.033)	(0.357)	(0.025)	(0.031)
μ_{20}		α_{20}	α_{21}	β_{21}
0.145		0.095	0.081	0.905
(0.075)		(0.045)	(0.018)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.Fr]-L1	0.185	0.233	0.668	0.521	400	400	0.566	0.707
ML: -3738.65	(0.101)	(0.046)	(0.054)	(0.045)	-	-	(0.005)	(0.011)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.537	0.064	0.607	0.085	0.899
(0.182)	(0.033)	(0.379)	(0.027)	(0.034)
μ_{20}		α_{20}	α_{21}	β_{21}
0.147		0.097	0.082	0.905
(0.075)		(0.047)	(0.018)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.Fr]-L1	0.144	0.230	1	0.527	400	400	0.566	0.023
ML: -3737.69	(0.246)	(0.046)	-	(0.044)	-	-	(0.005)	(0.040)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.541	0.066	0.602	0.081	0.905
(0.182)	(0.032)	(0.355)	(0.025)	(0.031)
μ_{20}		α_{20}	α_{21}	β_{21}
0.145		0.085	0.076	0.912
(0.074)		(0.043)	(0.016)	(0.019)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.Fr]-L1	0.186	0.278	0.627	0.391	400	400	0.566	0.945
ML: -3735.91	(0.054)	(0.063)	(0.037)	(0.087)	-	-	(0.005)	(0.012)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.505	0.069	0.606	0.088	0.898
(0.179)	(0.033)	(0.339)	(0.025)	(0.029)
μ_{20}		α_{20}	α_{21}	β_{21}
0.162		0.081	0.079	0.910
(0.074)		(0.041)	(0.017)	(0.020)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.UK-L4	0.224	0.228	0.514	0.730	400	400	0.566	1.21
ML: -3736.55	(0.049)	(0.081)	(0.040)	(0.046)	-	-	(0.004)	(0.023)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.529	0.066	0.663	0.092	0.893
(0.182)	(0.033)	(0.349)	(0.025)	(0.030)
μ_{20}		α_{20}	α_{21}	β_{21}
0.148		0.088	0.081	0.907
(0.075)		(0.043)	(0.017)	(0.020)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.UK-L4	-0.003	0.282	0.462	0.571	400	400	0.566	-1.159
ML: -3737.13	(0.10)	(0.049)	(0.097)	(0.038)	-	-	(0.005)	(0.024)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.509	0.072	0.651	0.087	0.897
(0.179)	(0.033)	(0.369)	(0.026)	(0.032)
μ_{20}		α_{20}	α_{21}	β_{21}
0.155		0.091	0.080	0.907
(0.071)		(0.026)	(0.017)	(0.020)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.UK]-L1	0.131	0.281	0.601	0.487	400	400	0.566	1.358
ML: -3738.22	(0.075)	(0.055)	(0.041)	(0.063)	-	-	(0.005)	(0.019)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.509	0.072	0.652	0.087	0.897
(0.179)	(0.033)	(0.360)	(0.025)	(0.030)
μ_{20}		α_{20}	α_{21}	β_{21}
0.156		0.091	0.080	0.907
(0.073)		(0.043)	(0.017)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[err.UK]-L1	0.131	0.281	0.602	0.487	400	400	0.566	1.844
ML: -3738.20	(0.077)	(0.057)	(0.042)	(0.063)	-	-	(0.004)	(0.026)

Mean Eq		Volatility Eq		
μ_{10}	μ_{13}	α_{10}	α_{11}	β_{11}
0.541	0.068	0.527	0.080	0.907
(0.157)	(0.033)	(0.398)	(0.031)	(0.037)
μ_{20}		α_{20}	α_{21}	β_{21}
0.149		0.089	0.081	0.907
(0.068)		(0.044)	(0.017)	(0.020)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[serr.UK]-L3	0.299	0.113	0.582	0.448	400	400	0.566	1.159
ML: -3737.59	(0.051)	(0.062)	(0.038)	(0.096)	-	-	(0.005)	(0.018)

E.3. Estimation Results of DSTCC Models not reported in Chapter 5

S&P-AG – S&P500

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.033	0.092	0.053	0.933
(0.066)	(0.012)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.175	0.072	0.077	0.909
(0.051)	(0.009)	(0.003)	(0.003)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.AG]-L2	0.035	-0.246	0.453	0.446	400	400	0.891	1.97
ML: -4705.05	(0.031)	(0.105)	(0.071)	(0.159)	-	-	(0.004)	(0.39)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.064	0.083	0.051	0.936
(0.061)	(0.011)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.182	0.071	0.077	0.909
(0.033)	(0.001)	(0.003)	(0.004)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
vol.AG-L4 + S[err.SP]-L4	-0.006	-0.141	0.140	0.541	400	400	5.70	5.64
ML: -4703.21	(0.036)	(0.081)	(0.043)	(0.064)	-	-	(0.295)	(0.266)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.049	0.086	0.051	0.936
(0.068)	(0.011)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.171	0.070	0.077	0.910
(0.003)	(0.002)	(0.003)	(0.002)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
vol.AG-L4 + S[serr.AG]-L2	0.026	-0.326	0.179	0.304	400	400	5.39	1.39
ML: -4706.69	(0.039)	(0.069)	(0.039)	(0.088)	-	-	(0.186)	(0.035)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.052	0.083	0.051	0.935
(0.058)	(0.005)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.185	0.071	0.077	0.909
(0.037)	(0.006)	(0.003)	(0.003)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
vol.SP-L2 + S[serr.AG]-L2	0.052	0.576	-0.399	0.483	400	400	3.95	9.89
ML: -4705.31	(0.000)	(0.049)	(0.188)	(0.354)	-	-	(18)	(0.53)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.061	0.093	0.049	0.935
(0.061)	(0.011)	(0.003)	(0.002)
μ_{20}	α_{20}	α_{21}	β_{21}
0.184	0.071	0.080	0.906
(0.000)	(0.000)	(0.000)	(0.003)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
vix-L2 + S[serr.AG]-L2	0.019	0.381	-0.355	-0.523	400	400	4.21	27.88
ML: -4706.23	(0.029)	(0.052)	(0.162)	(0.202)	-	-	(0.24)	(2.28)

S&P-PM – S&P500

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.009	0.087	0.102	0.881
(0.048)	(0.021)	(0.007)	(0.007)
μ_{20}	α_{20}	α_{21}	β_{21}
0.167	0.072	0.075	0.910
(0.006)	(0.000)	(0.002)	(0.005)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.PM-L2	-0.199	-0.393	0.204	1	2.47	400	0.856	0.482
ML: -4522.73	(0.057)	(0.083)	(0.109)	-	(0.49)	-	(0.056)	(0.023)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.004	0.089	0.103	0.880
(0.049)	(0.020)	(0.013)	(0.014)
μ_{20}	α_{20}	α_{21}	β_{21}
0.156	0.071	0.077	0.910
(0.051)	(0.013)	(0.005)	(0.003)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + serr.SP-L1	-0.105	-0.016	0.131	0.927	400	5.22	0.667	1.242
ML: -4521.43	(0.028)	(0.23)	(0.048)	(0.058)	-	(2.21)	(0.005)	(0.143)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
0.000	0.086	0.103	0.881
(0.049)	(0.002)	(0.001)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.159	0.067	0.074	0.912
(0.053)	(0.017)	(0.010)	(0.011)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + S[serr.SP]-L1	-0.077	-0.622	0.172	0.016	400	400	0.662	4.61
ML: -4522.27	(0.000)	(0.097)	(0.047)	(0.196)	-	-	(0.005)	(0.325)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
-0.003	0.083	0.105	0.880
(0.043)	(0.011)	(0.005)	(0.004)
μ_{20}	α_{20}	α_{21}	β_{21}
0.161	0.072	0.075	0.910
(0.000)	(0.005)	(0.003)	(0.003)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + A[err.PM]-L4	-0.131	0.042	0.711	0.225	400	400	0.887	1.153
ML: -4523.01	(0.041)	(0.041)	(0.045)	(0.002)	-	-	(0.005)	(0.012)

Mean Eq	Volatility Eq		
μ_{10}	α_{10}	α_{11}	β_{11}
-0.005	0.083	0.103	0.881
(0.051)	(0.027)	(0.018)	(0.019)
μ_{20}	α_{20}	α_{21}	β_{21}
0.176	0.071	0.078	0.908
(0.052)	(0.032)	(0.017)	(0.021)

Correlation Eq.

Transition Variables	ρ_{11}	ρ_{12}	ρ_{21}	ρ_{22}	γ_1	γ_2	c_1	c_2
Time + err.SP-L1	-0.053	-0.187	0.154	0.719	400	400	0.809	3.727
ML: -4528.89	(0.032)	(0.210)	(0.059)	(0.126)	-	-	(0.010)	(0.293)

APPENDIX F
ADDITIONAL TRANSITION VARIABLE TEST RESULTS NOT REPORTED IN CHAPTERS

F.1. LM_2 test results not reported in Chapter 3

Shgh-A – S&P500			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
A[err.Ch]-L2	Time	8.441	0.004
A[serr.Ch]-L2	Time	6.174	0.013
S[serr.Ch]-L2	Time	9.598	0.002
err.US-L1	Time	9.817	0.002
serr.Ch-L1	Time	5.408	0.020
Shgh-A – FTSE			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
A[serr.Ch]-L2	Time	9.539	0.002
Shgh-A – CAC			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
A[err.Ch]-L2	Time	7.329	0.007
A[serr.Ch]-L2	Time	8.509	0.004
Shgh-A – Nikkei			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
err.HK-L2	Time	5.925	0.015
serr.HK-L2	Time	6.618	0.010
Shgh-B – S&P500			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
err.US-L2	Time	7.090	0.008
serr.US-L2	Time	7.336	0.007
err.HK-L2	Time	8.974	0.003
serr.HK-L2	Time	9.431	0.002
A[err.Jap]-L3	Time	12.467	0.000

Shgh-B – FTSE			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
Time	A[err.UK]-L2	6.901	0.008
serr.UK-L2	A[err.UK]-L2	6.536	0.010
err.US-L2	A[err.UK]-L2	3.303	0.069
A[serr.US]-L2	A[err.UK]-L2	4.906	0.027
err.HK-L2	A[err.UK]-L2	10.90	0.000
A[serr.HK]-L1	A[err.UK]-L2	5.210	0.022
A[serr.Jap]-L1	A[err.UK]-L2	9.565	0.002
⋮			
Shgh-B – CAC			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
Time	A[serr.US]-L2	10.322	0.001
A[err.Fr]-L2	A[serr.US]-L2	3.057	0.080
serr.US-L2	A[serr.US]-L2	0.021	0.885
S[err.Jap]-L3	A[serr.US]-L2	5.384	0.020
⋮			
Shgh-B – Nikkei			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
err.HK-L2	serr.US-L2	5.747	0.016
A[serr.US]-L1	serr.US-L2	4.631	0.031

F.2. LM_2 test results not reported in Chapter 4

ISX100 – DAX			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
serr.Tr-L2	Time	27.344	0.000
A[serr.Tr]-L4	Time	18.604	0.000
S[err.Ger]-L3	Time	20.108	0.000
S[err.Fr]-L3	Time	21.934	0.000
A[err.UK]-L2	Time	23.774	0.000
⋮			
ISX100 – CAC			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
S[err.Tr]-L4	Time	27.016	0.000
S[err.US]-L3	Time	32.976	0.000
vol.Ger-L2	Time	25.777	0.000
A[err.UK]-L2	Time	30.202	0.000
⋮			

ISX100 – FTSE			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
S[err.Tr]-L4	Time	32.120	0.000
vol.Tr-L2	Time	13.848	0.000
S[err.Ger]-L3	Time	34.296	0.000
S[err.Fr]-L3	Time	34.279	0.000
A[err.UK]-L2	Time	28.027	0.000
ISX100 – S&P500			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
A[err.Tr]-L4	Time	5.394	0.020
S[err.Ger]-L3	Time	11.293	0.000
S[serr.Fr]-L3	Time	15.173	0.000
S[serr.UK]-L3	Time	13.916	0.000

F.3. LM_2 test results not reported in Chapter 5

S&P-PM – S&P500			
1^{st} Transition Variable	Additional Transition Variable	LM-stat.	p-value
err.PM-L2	Time	11.468	0.001
serr.PM-L2	Time	12.155	0.000
err.SP-L1	Time	13.119	0.000
serr.SP-L1	Time	13.656	0.000
A[err.PM]-L2	Time	9.449	0.002
S[err.PM]-L2	Time	7.944	0.005
S[serr.SP]-L1	Time	14.731	0.000

APPENDIX G

EVIDENCE OF INCREASING TREND IN CONDITIONAL CORRELATION OF CHINESE STOCK MARKETS WITH OTHERS NOT REPORTED IN CHAPTER 3

	Shgh-A		Shgh-B	
	LM-statistics	p-value	LM-statistics	p-value
DAX	6.761	0.009	1.309	0.252
Sing	17.84	0.000	1.117	0.290
Taiw	21.23	0.000	2.305	0.128
HSI	45.09	0.000	1.529	0.216
ASX	16.98	0.000	4.832	0.027
Kospi	14.25	0.000	11.47	0.001

APPENDIX H
CURRICULUM VITAE

PERSONAL INFORMATION

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EDUCATION

Degree	Institution	Year of Graduation
Ph.D. in Economics	METU, Economics	2013
B.Sc in Economics	METU, Economics,	2004

TITLE OF Ph.D. THESIS: Modeling Co-movements among Financial Markets: Applications of Multivariate Autoregressive Conditional Heteroscedasticity with Smooth Transition in Conditional Correlations

RESEARCH AND TEACHING FIELDS:

Econometrics, International Finance, and Applied Linear and Non-linear Time Series

EMPLOYMENT RECORD

2005 – Present: Teaching & Research Assistant, Department of Economics, Middle East Technical University, Ankara, Turkey.

PUBLICATIONS

Working Papers:

1. Öztek, M. Fatih and Öcal, Nadir (2013) "Financial Crises, Financialization of Commodity Markets and Correlation of Agricultural Commodity Index with Precious Metal Index and S&P500"

2. Öztek, M. Fatih and Öcal, Nadir (2012) "Integration of China Stock Market with International Stock Markets: An Application of Smooth Transition Conditional Correlation with Single and Double Transition Functions."

3. Öztek, M. Fatih and Öcal, Nadir (2012) "The Origins of Increasing Trend in Correlations among European Stock Markets: Evidence from Smooth Transition Conditional Correlation Approach."

4. Öztek, M. Fatih and Öcal, Nadir (2011) "Integration of Turkish Stock Market with European Stock Markets: Nonlinear Time Varying Correlation Approach."

CONFERENCE PRESENTATIONS

1. (December, 2011) "The Origins of Increasing Trend in Correlations among European Stock Markets: Evidence from Smooth Transition Conditional Correlation Approach." 5th CSDA International Conference on Computational and Financial Econometrics (CFE'11) 17-19 December 2011, Senate House, University of London, UK

2. (October, 2011) "Integration of China Stock Market with US Stock Market: An Application of Smooth Transition Conditional Correlation with Double Transition Functions." 2011 Meetings of the Midwest Econometrics Group October 6-7, The Booth of School of Business, University of Chicago.

3. (June, 2011) "Integration of Turkish Stock Market with European Stock Markets: Nonlinear Time Varying Correlation Approach." Anadolu International Conference in Economics June 15-17, 2011 Eskişehir.

SEMINAR PRESENTATIONS

(October, 2011) "Integration of Turkish Stock Market with European Stock Markets: Nonlinear Time Varying Correlation Approach." Seminar series in Department of Economics, Middle East Technical University.

WORKSHOP PARTICIPATIONS

(May, 2011) Interdisciplinary Workshop on "Econometric and Statistical Modeling of Multivariate Time Series" Universite Catholique de Louvain (UCL) Louvain-la-Neuve (Belgium)

APPENDIX I
TURKISH SUMMARY

Giriş ve Literatür Özeti

Son otuz yıl finans piyasalarında çok dramatik çöküşlere tanıklık etmiştir. Bunların ilki ve en etkilisi 19 Ekim 1987 de gerçekleşen hisse senedi piyasaları tarihinin en büyük bir günlük yüzde düşüşünün kaydedildi ve "Kara Pazartesi" olarak bilinen çöküştür. (1987 Ekim'inde hisse senedi borsaları Hong Kong'da %45.5, Fransa'da %23.15, Almanya'da %22.5, ABD'de %23 ve İngiltere'de % 27.3 düşmüştür.) Kronolojik olarak, ikinci sırada uluslararası finans piyasalarında uzun süreli dalgalanmalara neden olan 1992 yılında gerçekleşen "Kara Çarşamba" gelmektedir. Bu krizin olumsuz etkileri 1993 yılı sonuna kadar varlığını muhafaza etmiştir. Ardından, ünlü 1997 Asya finansal krizi ve 1998 Rusya mali krizi dünya finans piyasalarını vurmuş ve yıkıcı dalgalanmalar oluşturmuştur. Yirminci asrın sonu küresel krizlerin sonu olmamış ve yeni milenyum artan volatilite (oynaklık) ve büyük zararlar ile 2001 yılında patlayan internet şirketleri balonu ile gelmiştir. 2002 ve 2008 yılları arasında nispeten istikrarlı bir artış trendi yaşanırken, Amerikan bankacılık sisteminin likidite sorunları ve Avrupa borç krizi neticesinde finans piyasaları çok kırılgan ve kötü haberlere duyarlı hale gelmiş ve piyasalardaki volatilite önemli oranda tekrar artmıştır. Çok kısa özet olarak listesini verdiğimiz bu büyük finansal çöküşler kökenleri ve sebepleri bakımından farklılık göstermekle birlikte, etkileri sınırları ötesine gitmiş ve dünyadaki tüm finansal piyasalarda yüksek fiyat dalgalanmaları üretmişlerdir.

Bu kriz dönemlerinde, uluslararası finans piyasalarına ait günlük fiyat verilerinin basit grafiksel analizi bu piyasalarda eşanlı önemli fiyat değişimleri olduğu gerçeğini ortaya koymaktadır. Bu tür grafiksel analizler finans piyasaları arasındaki ortak hareketlerin zamanla arttığı ve çok güçlü hale geldiği görüşünü desteklemektedir. Bu nedenle, ortak hareketlerin analizi ulusal finans piyasalarının günlük performans değerlendirmesinde ve tahmininde finans piyasalarının küreselleşmesi sürecini doğuran etkenleri[4] kullanarak finansal piyasalar arasındaki ortak fiyat hareketlerini rasyonalize etmeye çalışan piyasa katılımcıları, medya ve politika yapıcılar tarafından yaygın olarak kullanılan bir araç haline gelmiştir.

Her incelemenin onunla başlamasına rağmen, verilerin görsel olarak incelenmesi grafiksel analizler sonucu elde edilen çıkarımların doğrulanması için gerekli olan

[4]Bu etkenler bilgi teknolojisindeki gelişmeler, çok uluslu şirketlerin kurulması, finansal sistemlerin ve sermaye piyasalarının serbestleşmesi ve döviz kontrollerinin kaldırılması olarak özetlenebilir.

biçimsel kontrollerin yerini tutması mümkün değildir. Yani, finans piyasaları arasındaki ortak hareketlerde gözlemlenen artış ölçülmeli ve istatistiksel teknikler ile test edilmelidir. Ortak hareketlerin doğal bir istatistiksel ölçüsü seriler arasındaki bağımlılığın ölçekten bağımsız bir ölçüsü olan korelasyondur. Korelasyon sırasıyla, negatif ve pozitif ilişkileri gösteren -1 ile 1 arasında değerler alır. Dolayısıyla, finans piyasaları arasındaki ortak hareket bu piyasalar arasındaki korelasyonun modellenmesi ile incelenebilir.

Uluslararası finans piyasaları arasındaki ortak hareketlerin veya korelasyonun düzeyi finans teorisi için çok önemli anlama sahip olmakla birlikte finansal karar verme sürecinde çok önemli bir girdidir. Önemi istatistikçilerin ve ekonometricilerin riskin ölçüsü olarak ikinci momenti kullanmalarından kaynaklanmıştır. Riskin tanımı üzerinde genel bir anlaşma olmamasına rağmen, tam bilgi ortamının eksikliği nedeniyle gelecekteki koşulların belirsizliği ile ilişkilendirilir ve genellikle belirsizliğin hedefler üzerindeki etkisi olarak tanımlanır. Yatırımcılar servetlerini maksimize etmek amacı ile finansal varlıkları alıp satarlar. Ancak bu varlıkların getirisi yatırım kararının alındığı tarihde bilinmesi mümkün olmayan varlığın gelecekteki fiyatına bağlıdır. Varlığın fiyatı artabilir veya azalabilir ama bugünün ve geçmişin bilgileri ile gelecekteki fiyatı tam olarak tahmin etmek de mümkün değildir. Varlıkların gelecekteki fiyatları üzerindeki bu belirsizlik yatırımcıların hedeflerini etkiler ve tanıma göre, finansal piyasaları çok riskli hale getirir.

Tipik bir yatırımcı istenmeyen kötü sonuçlar üretebilme kapasitesine sahip risk ile karşı karşıya gelmeyi tercih etmez. Bu nedenle yatırımcıların yüksek getiriye sahip ama riski düşük varlıkları seçebilmek için elde edilebilir varlıkları karşılaştırmaları gerekir. Serveti maksimize etmek amacı doğrultusunda, yüksek getiri her zaman arzu edilir ama varlıkların kalıtsal risk-getiri ikilemi (risk-return trade-off) nedeniyle yüksek getiri yüksek risk düzeyi ile birlikte gelir. Bir başka ifadesiyle, risk daha yüksek getirinin maliyeti olarak düşünülebilir. Bu nedenle yatırımcıların getirilerini maksimize etmek ve risklerini en aza indirmek için yatırım kararlarını optimize etmeleri gerekmektedir.

Bu optimizasyon probleminin pratik, kolay ve en eski çözüm yöntemi insanoğlunun bilgeliğinin ürünü olan “Tüm yumurtaları bir sepete koyma” deyimi ile özetlenebilir. En genel hali ile bu çözüm yöntemi temelinde belirsizlik yatan tüm alan ve konulara uyarlanarak uygulanması mümkündür. Bu yöntemin finans teorisi için özel bir hali "Portföy Çeşitlendirilmesi" adı ile Markowitz (1952) tarafından bu alanda çığır açan “Portföy Seçimi” makalesinde formüle edilmiştir. Markowitz çeşitli varlıklara yatırım yaparak varlıkların bireysel öz risklerinden daha düşük risk seviyesine sahip bir portföy oluşturmanın mümkün olduğu gerçeğinden yola çıkarak belirli bir getiri düzeyi için portföy riskini en aza indirerek mümkün olan en iyi portföyün nasıl oluşturulacağını göstermiştir. Bu riski en aza indirme probleminin neticesi olarak portföy

içerisindeki her bir varlığın optimum ağırlığı hesaplanır. Markowitz'in ortaya koyduğu bu yöntemde riskin ölçüsü olarak varyans kullanılmaktadır. Dolayısıyla riski minimize etmek portföyün varyansını en aza indirmek ile eşdeğerdir. Yatırımcıların oluşturacakları portföye ait varyansı hesaplıyabilmeleri için portföyü oluşturan tüm varlıkların varyanslarına ve varlıklar arasındaki tüm kovaryanslara veya korelasyonlara ihtiyacı vardır. Portföyü oluşturan varlıklar arası korelasyonlar ile portföy varyansı arasındaki ilişkinin pozitif olmasından ötürü, portföy çeşitlendirme yöntemi ile daha düşük risk seviyesine ulaşmanın mümkün olabilmesi için varlıklar arasında korelasyonların düşük ya da negatif olması gerekir.

Tek piyasa içerisinde yapılacak olan Portföy Çeşitlendirme yönteminin bu piyasanın ve bu piyasanın faaliyet gösterdiği ekonominin ortak dinamikleri tarafından üretilen sistematik riski yok etmesi mümkün değildir. Dolayısıyla, yurtiçi sistematik riski azaltabilmek için, portföy çeşitlendirme stratejilerinin kapsamı uluslararası ölçeğe genişletilmiştir. Solnik (1974) tarafından gösterildiği gibi, ülkelerin ekonomik büyüme seviyeleri ve iş döngülerinin (business cycle) zamanlamaları arasında farklılıkların mevcut olması nedeniyle uluslararası çeşitlendirme yöntemi daha düşük risk seviyelerine ulaşılabilmesine olanak sağlamaktadır.

Bu nedenle, daha yüksek getiri oranlarına bağlı düşük risk yükünü arayan ve riskten kaçınan tipik bir yatırımcının uluslararası finans piyasaları arasındaki korelasyonun yapısını ve özelliklerini bilmesi uluslararası portföy çeşitlendirme yöntemlerinin potansiyel yararlarını değerlendirebilmesi için çok büyük bir önem arzetmektedir. Bu durum, pek çok akademisyen için motivasyon kaynağı olmuş ve ampirik literatürde finans piyasaları arasındaki korelasyonun incelenmesine olan ilgi her geçen gün artmaktadır. Bu literatürde, pek çok değişik ülkerin ve bölgelerin finans piyasaları arasındaki korelasyon yapıları çeşitli modellerle zamanla değişen korelasyon çerçevesinde incelenmiştir.

Finans piyasalarına ait günlük gözlemlerden bariz bir şekilde ortada olmasına rağmen, ampirik sonuçlar 2000'lere kadar finans piyasaları arasındaki ortak hareketlerin zamanla güçlendiği veya artan bir trend gösterdiği sonucunu desteklememektedir. King ve Wadhwani (1990) uluslararası hisse senedi piyasalarının volatilitelerinin bulaşıcılığını araştırmak amacıyla İngiltere, ABD ve Japonya'daki borsa endeksleri arasındaki korelasyon dinamiklerini incelemiştir. Temmuz 1987-Şubat 1988 arası dönemde saatlik getiri verilerini kullanarak, endeksler arasındaki korelasyonların zaman içerisinde sabit olmadığını, yani zamanla değiştiğini ve korelasyonların yüksek volatilite dönemlerinde artış eğiliminde olduğunu gösteren kanıtlar bulmuşlardır. Hisse senedi piyasaları arasındaki korelasyonların bağlantılarını ve uzun dönem özelliklerini araştırmak için King ve ark. (1994) kapsadığı zaman aralığı ve endek sayısı açısından bu korelasyon analizini genişletmiştir. Çok değişkenli faktör modeli kapsamında, Ocak, 1970-Ekim, 1988 tarihleri arası dönem için 16 ülke (Avustralya,

Avusturya, Belçika, Kanada, Danimarka, Fransa, Almanya, İtalya, Japonya, Hollanda, Norveç, İspanya, İsveç, İsviçre, İngiltere ve ABD) hisse senedi piyasasına ait aylık getiri verilerini kullanmışlardır. Korelasyonların sabit olmadığını ve volatilite ile bağlantılı olduklarını belgelemiş ancak oynaklık ile korelasyon arasında nedensel bir ilişki tespit edememişlerdir. Ayrıca endeksler arasındaki korelasyonların uzun dönem özelliklerini ortaya çıkarmak için artan trend için ip uçları araştırmışlar ama 18 yıllık bu süre içinde herhangi bir kanıt bulamamışlardır. Borsa endeksleri arasındaki korelasyonlarda artan trend bulan önceki çalışmalara (örneğin VonFurstenberg ve Jeon (1989)) ait bulguların 1987 finansal çöküşünü çevreleyen gözlemlere bağlı olduğunu ve dolayısıyla bu bulguların korelasyonlarda kalıcı yerine geçici artışı yansıttığı sonucuna varmışlardır.

Yüksek frekanslı veri ile, ABD ve Japonya'daki hisse senedi piyasaları arasındaki ortak hareketler 31 Mayıs 1988 (1987 finansal çöküşü sonrası) tarihinden 29 Mayıs 1992 tarihine kadar olan süre için Karolyi ve Stulz (1996) tarafından incelenmiştir. Mevcut literatür bulgularına ek olarak, S&P500 ve Nikkei endekslerine gelen büyük şokların endeksler arasındaki korelasyonun kalıcılığını olumlu yönde etkilediğini ortaya koymuşlardır.

Ocak 1960'dan Ağustos 1990'a kadar 30 yıllık bir süre için Longin ve Solnik (1995) aylık veri kullanarak başlıca gelişmiş ülkelerin (Fransa, Almanya, İsviçre, İngiltere, Japonya, Kanada ve ABD) hisse senedi borsa endeksleri arasındaki koşullu korelasyonları modellemişlerdir. Benzer bir çalışmada, Ramchand ve Susmel (1998) ABD ve dört gelişmiş ülke (Japonya, İngiltere, Almanya ve Kanada'nın) endeksleri arasındaki koşullu korelasyonları Ocak 1980-Ocak 1990 tarihleri arası dönem için haftalık veri kullanarak modellemişlerdir. Bu iki çalışma koşullu korelasyonun dinamik yapısını çok değişkenli genelleştirilmiş otoregresif koşullu değişen varyans (MGARCH) kapsamında incelemiştir. İlki çok değişkenli GARCH (1,1) modelini yedi endeks için kullanırken, diğeri iki değişkeli switching ARCH (SWARCH) modelini kullanmayı tercih etmiştir. Her iki çalışmada korelasyonun yüksek oynaklık dönemlerinde arttığı sonucuna varmıştır. Daha spesifik olarak, Ramchand ve Susmel (1998) ABD hisse senedi piyasasında volatilitenin yüksek olduğu dönemlerde düşük olduğu dönemlere kıyasla ABD ve diğer endeksler arasındaki korelasyonların ortalama olarak 2 ila 3,5 kat daha yüksek olduğunu rapor etmişlerdir.

Bu ampirik sonuçlar finans piyasaları arasındaki korelasyonun dinamik bir yapıya sahip olduğunu saptamışlardır. Özetle, korelasyon zaman içerisinde değişen ve yüksek oynaklık dönemlerinde artan bir yapıya sahiptir. Fakat Longin ve Solnik (2001) ve Ang ve Bekaert (2002) korelasyonun oynaklığa verdiği tepkinin asimetrik olduğunu rapor etmiş ve boğa piyasalarında değilde ayı piyasaları esnasında artığı sonucunu ortaya çıkarmışlardır.

2000 yılından sonra, literatürde bulgular finans piyasaları arasındaki korelasyonun zamanla artma eğiliminde olduğunu göstermektedir. Bu sonuç, gelişmiş ülkeler arasında ve aynı bölge ülkeleri arasında daha belirgindir. Korelasyon düzeyi ülkeden ülkeye ve bölgeden bölgeye değişmekle birlikte en yüksek seviyenin Avrupa Birliği (AB) üyesi gelişmiş ülkeler arasında gözlendiği Cappiello ve ark. (2006) tarafından belgelenmiştir. 8 Ocak 1987'den 7 Şubat 2002'ye kadar haftalık veri kullanarak, Avrupa, Amerika ve Avusturalya'da (Avrupa; Avusturya, Belçika, Danimarka, Fransa, Almanya, İrlanda, İtalya, Hollanda, Norveç, İspanya, İsveç, İsviçre ve İngiltere, Avustralya; Avustralya, Hong Kong, Japonya, Yeni Zelanda ve Singapur, ve Amerika; Kanada, Meksika ve ABD.) 21 ülke hisse senedi ve tahvil piyasalarının korelasyon yapısını incelemişlerdir. Engle (2002) geliştirdiği Dinamik Koşullu Korelasyon GARCH (DCC-GARCH) modelinin asimetrik ve genelleştirilmiş sürümünü öneren Cappiello ve ark. (2006) ağırlıklı olarak Avrupa'daki finans piyasaları arasındaki korelasyonun artan trend gösterdiğine dair kanıtlar bulmuş ve Avrupa Para Sistemi (EMS) üyesi ülkeler arasında ortak para birimi Euro'nun kullanılmaya başlandığı tarihe denk gelen Ocak 1999 tarihinde endeksler arası korelasyonlarda yapısal bir kırılmanın var olduğunu tespit etmişlerdir. Ancak Avustralya, Amerika ve Avrupa grupları arasındaki korelasyonun Euro bölgesindeki gelişmelerden etkilenmemiş gibi göründüğünü rapor etmişlerdir. Euroya geçilmesinin hemen ardından euronun ABD doları karşısında değer kaybetmesinin sebebinin EMS üyesi ülkelerin hisse senedi piyasaları arasındaki korelasyonun artışı olabileceği iddia edilmektedir.

Cappiello ve ark. (2006) dan farklı olarak, Kim ve ark. (2005) Ocak 1989-Mayıs 2003 arasını kapsayan dönem için EMS üyesi ülkeler, Japonya ve ABD'deki hisse senedi piyasalarının günlük verilerine zamanla değişen koşullu korelasyon yapısına sahip iki değişkenli EGARCH modelini uygulamış ve euronun kullanılmaya başlandığı tarihten itibaren artan trendin tüm uluslararası hisse senedi piyasaları arası korelasyonlar için geçerli olduğu sonucunu bulmuşlardır. Benzer sonuçlar Aralık 1990-Ağustos 2004 arası dönem için İngiltere, Almanya, Fransa ve ABD'deki borsa endekslerinin günlük verilerine çok değişkenli DCC-GARCH modelini uygulayan Savva ve ark. (2009) trafından da elde edilmiştir. Cappiello ve ark. (2006) ile karşılaştırıldığında son iki çalışmada daha uzun ve daha yüksek frekanslı örneklemin kullanılıyor olması tek para biriminin euro alanı içerisindeki ve dışırısındaki ülkelerde işlem gören borsa endeksleri arasındaki korelasyon üzerindeki etkilerini yakalama imkanı verdiği görünmektedir.

Silvennoinen ve Teräsvirta (2009) DAX, CAC40, FTSE ve HSI endeksleri arasındaki koşullu korelasyonun özelliklerini Aralık 1990'nın ilk haftası ile Nisan 2006'nın son haftası arası dönem için haftalık verileri kullanarak incelemişlerdir. Yazarlar koşullu korelasyon denklemi için yumuşak geçiş tanımlayarak çok değişkenli GARCH modelleri çerçevesinde zamana göre değişen koşullu korelasyon yaklaşımını kullanmış ve bu borsa endeksleri arasındaki korelasyonların 1999 baharında yüksek düzeylere çık-

tığı sonucuna varmışlardır. Ayrıca CAC-DAX, CAC-FTSE ve DAX-FTSE arasındaki artan koşullu korelasyonların 1999 yılından bu yana endekslerin volatilite seviyelerinden etkilendiğini ortaya koymuşlar ve yeni yüzyılla birlikte, CAC-DAX, CAC-FTSE ve DAX-FTSE arasındaki korelasyonun sırasıyla 0.9, 0.85 ve 0.8 mertebelerini geçtiğini, ama HSI ve diğer endeksler arasındaki koşullu korelasyonların 0.55 seviyelerinde kaldığını rapor etmişlerdir. Benzer bir çalışmada, Aslanidis ve ark. (2010), S&P500 ve FTSE endeksleri arasındaki korelasyon yapısını analiz ettikleri çalışmalarında koşullu korelasyonun artan trende sahip olduğunu ve Şubat 2000 tarihinde 0.9 seviyelerine kadar yükseldiğini rapor etmişlerdir. Buna ek olarak yazarlar hisse senedi piyasalarının oynaklığının korelasyon üzerindeki rolünü de araştırmış ve volatilitenin 2000 yılı öncesinde önemli bir rol oynadığını ama korelasyonun yüksek seviyelere (0.9) çıkmasını takiben önemini kaybettiği sonucunu bulmuşlardır.

Özetle, gelişmiş ülkelerin finans piyasaları arasındaki korelasyonun çok yüksek olduğu ve dolayısıyla bu pazarlar arasında yapılacak bir portföy çeşitlendirmesinin sağlayacağı faydanın çok sınırlı olacağı artık iyi bilinen bir gerçektir. Bu durum yatırımcıları gelişmiş piyasalar ile korelasyonu düşük (mümkünse negatif) ama yüksek büyüme potansiyeli olan alternatif pazar arayışına yönlendirmektedir.

Bu tez çalışması kapsamında, iki farklı gelişmekte olan ülkede işlem gören hisse senedi piyasaları ile iki emtia piyasası gelişmiş ülkelerdeki piyasalara alternatif olarak değerlendirilmiştir. Gelişmekte olan ülke olarak, Türkiye ve Çin 2000'li yılların ortalarından bu yana göstermiş oldukları gelecek vaat eden büyüme performansları nedeniyle tercih edilmiştir. Emtia piyasaları arasından, tarımsal ürün ve kıymetli metal piyasaları ilkinin sergilemiş olduğu olağanüstü performans ve ikincisinin sahip olduğu "güvenli liman" özelliği nedeniyle seçilmişlerdir. Gelişmiş ülkelerdeki hisse senedi piyasaları ile bu alternatif piyasalar arasındaki bağımlılığın yapısı ve özellikleri finans piyasaları arasındaki koşullu korelasyonların zamanla değiştiği gerçeğini göz önüne alabilme kapasitesine sahip çok değişkenli genelleştirilmiş otoregresif koşullu değişen varyans (MGARCH) modelleri bağlamında incelenmiştir. Dinamik korelasyonların modellenmesi ile, portföy çeşitlendirilme yöntemiyle oluşturulacak olan en iyi portföyün sahip olduğu optimal ağırlıkların hesaplanabilmesi için kullanılan korelasyon seviyeleri ortaya çıkarılmış olacaktır. Korelasyon seviyesinin yanı sıra, korelasyonun dinamik yapısı ve özellikleri de portföy çeşitlendirme stratejileri için çok değerli bilgiler taşımaktadır. Alternatif piyasanın (örneğin Türkiye'deki hisse senedi piyasasının) gelişmiş piyasalarla olan koşullu korelasyonu küresel ölçekli kriz dönemlerinde artış eğilimi gösteriyor ise Türkiye borsasının ulaslararası yatırımcıların portföylerine dahil edilmesi volatilitenin yüksek olduğu dönemlerden ziyade düşük olduğu dönemlerde faydalı olacaktır. Dolayısıyla, bu koşullar altında kriz dönemlerinde hisse senedi piyasasına sermaye girişi pek olası değildir. Bu amaçla, küresel volatilitenin, piyasanın öz volatilitesinin ve piyasa koşularının piyasalar arasındaki korelasyonun dinamik yapısını açıklamadaki rolü de incelenmiştir.

Bu tez çalışmamız Türkiye ve Çin hisse senedi piyasalarının ve tarımsal ürün ve değerli metal piyasalarının getiri korelasyonlarının bağımsız ve kendi içinde bütün üç bölümde kapsamlı analizini sunmaktadır. Dolayısıyla çalışmamız bu piyasaların uluslararası yatırımcılara portföylerinin taşıdığı riski azaltabilmeleri için fırsatlar sunabilmesinin mümkün olup olmadığını araştırmak için bir girişim olarak değerlendirilebilinir.

Yöntem

Tüm ekonomik kararların doğasında yatan risk-getiri ikilemi gelecek üzerindeki belirsizlik tarafından oluşturulan riskin doğasının anlaşılmasını gerektirmektedir. Varlıkların, portföylerin ya da piyasaların riski gözlemlenemeyen volatilite kavramıyla ifade edilmektedir. Risk ile başa çıkmak için finans kuramı tarafından önerilen temel araçlar volatilite kavramının ikinci moment ile tam olarak ölçülebileceği varsayımını yaparak varyansın karekökünü volatilite ölçüsü olarak kullanmaktadır. Granger (2002) bu varsayımın geçerliliğini irdeleyerek varyansın başarılı bir risk ölçeği olabilmesi için yatırımcıların fayda fonksiyonlarının karesel veya varlıkların getiri dağılımının normal veya log-normal olması gerektiğini ortaya koymuştur. Bu çalışmasında Granger finansal serilerin çoğunun normal dağılıma göre aşırı basık bir dağılıma sahip olduğu Mandelbrot (1962) tarafından belgelendiğinden beri iyi bilinen bir gerçek olması nedeniyle ve Harter (1977), Para ve ark. (1982), Nyquist (1983), Ding ve ark. (1993) ve Granger (2000) tarafından yapılan çalışmalara da dayanarak riskin ölçeği olarak mutlak sapmanın ortalama değerinin kullanılmasını önermektedir. Risk ölçümü üzerindeki teorik tartışmaların devam etmesine rağmen, ampirik literatürde varyansın, kovaryansın ve eşdeğeri korelasyonun başarılı modellemesi ilgi odağıdır.

İstatistikçiler ve ekonometriciler varyansı tahmin etmek için çeşitli modeller önermişlerdir. Volatilite sabit olsa, geleneksel ekonometrik yöntemler volatilitenin göstergesi olan varyansı ortalama denklem ile birlikte başarılı bir şekilde tahmin edebilir. Ne yazık ki, finansal zaman serilerinin volatiliteleri yatırımcıların bir varlığı sonsuza kadar tutmak istimiyor olmaları nedeniyle odaklandıkları kısa vadede sabit değildir. Dolayısıyla, volatilitenin başarılı bir ölçüsü onun zaman içerisinde değişen doğasını yansıtabilmelidir.

Önerme enflasyon belirsizliğinin iş döngüsü üzerindeki etkilerini test etmek için zaman içinde değişen varyans modeli arayan Engle (1982)'den gelmistir. Zaman içerisinde değişen varyans ekonometri için o zamanda yeni bir kavram değildi ve regresyon analizi bağlamında heteroscedasticity olarak bilinmekteydi. Ancak bu durum geleneksel modellerde bağımsız değişkenlerin fonksiyonu olarak tanımlanırdı. Engle ise çığır açan çalışmasında önerdiği Otoregresif Koşullu Değişen varyans (ARCH) modeli ile ortalama denklemi ile birlikte değişen varyans denklemini otoregresif

hareketli ortalama (ARMA) modelleri ile ifade ederek başarılı bir şekilde tahmin edilebileceğini göstermiştir.

Burada iki nokta üzerinde daha fazla durulması gerekmektedir. Birincisi bu yeni modelin, koşulsuz varyans yerine koşullu varyansı vurguluyor olmasıdır. Bu durum tipik bir yatırımcının bir varlığı gelecekte daha yüksek bir fiyata satarak kar elde etmek amacıyla bugün satın alması gerçeğinden kaynaklanmaktadır. Yani yatırımcı bu varlığı sonsuza kadar elinde tutma maksadıyla almamaktadır. Bu nedenle, yatırımcı için bağlayıcı olan risk bu varlığı elde tutmayı planladığı süre zarfında taşıdığı risktir. Bir başka ifadesiyle yatırımcı bu varlığın uzun vadede sahip olduğu koşulsuz varyansı ile ilgilenmemektedir. Rasyonel bir yatırımcının ulaşabileceği mevcut tüm bilgileri kullanarak ortalama ve varyans denklemlerini tahmin etmesi gerekir. Dolayısıyla bağlayıcı olan koşullu tahminlerdir, koşulsuz olanlar değil. Ayrıca, koşullu yaklaşım kestirim (estimation) yöntemi için çok önemli bir anlam içerir. Herhangi bir olabilirlik fonksiyonu koşullu yoğunluklara ayrılabilir. Böylece koşullu varyans ile olabilirlik fonksiyonunu formüle etmek kolaydır ve maksimum olabilirlik ile kestirimi yönetmek daha kolaydır. Başka bir önemli nokta da, koşullu varyansı zamanla değişen bir serinin sabit koşulsuz varyansa sahip olmasının mümkün olmasıdır. Dolayısıyla sadece koşullu varyansın sabit olmaması serinin durağanlık özelliğini bozmadığı için ARCH süreçleri uygulanabilir ve anlamlı bir tahmin süreci temin etmektedir.

İkinci nokta ise ARCH/GARCH modellerinin koşullu varyans denklemini otoregresif (AR), hareketli ortalama (MA) veya otoregresif hareketli ortalama (ARMA) süreçleri olarak formüle edilebilmesine olanak sağlamasıdır. Bu nokta serinin kendisi olmasa bile serinin karesinin ve/veya mutlak değerlerinin otokorole olabileceğini ortaya koyan Granger'in önceki çalışmalarından ilham almıştır. Bu bulgunun regresyon modeli çerçevesindeki anlamı artıkların (residual) kendisi otokorole olmasa bile, artıkların karesi yada mutlak değeri otokorole olmasıdır. Bu durum bir çok finansal değişken için geçerlidir. Bu sonuç hata teriminin varyansının tahmin edilebilir olduğunu ifade etmektedir. Bir regresyon denklemi tahmin edilebilir bir sistematik bileşen ve tahmin edilmesi mümkün olmayan bir rasgele bileşenden oluşur. ARCH modelleri bu öngörülemeyen bileşenin (artıkların) varyansını yani hangi aralıkta değer aldığını öngörülebilir yapmaktadır.

Literatürde finansal verilere ait kovaryansın varyansda olduğu gibi zamanla değişen dinamik bir yapıya sahip olduğu iyi bilinen bir gerçektir. Dolayısıyla literatürde korelasyonun modellenmesinde kullanışlı (practical) yöntem, zamana bağlı değişen varyansın modellenmesinde çok başarılı olan ARCH/GARCH tipi modellerin çok değişkene genişletilmiş halidir. Çok değişkenli GARCH yapısında korelasyonu (kovaryans yerine) doğrudan formüle eden ilk model Bollerslev'in sabit koşullu korelasyon modelidir. (Constant Conditional Correlation, CCC, 1990). Bu modelde varyans ve kovaryans zaman içerisinde değişirken korelasyon sabit kalmaktadır.

Fakat sabit koşullu korelasyon varsayımının hisse senedi borsaları için geçerli olmadığı ve dinamik bir yapıya sahip olduğu Tse (2000) ve Bera ve Kim (2002) tarafından gösterilmiştir.

Engle (2002) korelasyon için GARCH tipi dinamik bir yapı tanımlayarak dinamik korelasyon yapısına sahip yeni bir model geliştirmiş ve modele dinamik koşullu korelasyon (Dynamic Conditional Correlation, DCC) adını vermiştir. Bu modelde iki aşamalı tahmin yöntemi kullanılmaktadır. Birinci aşamada her seri için ayrı ayrı tek değişkenli GARCH tahmini yapılmakta ve ikinci aşamada ise birinci aşamadan elde edilen standart hale getirilen hata terimleri kullanılarak korelasyon tahmin edilmektedir. Bu iki aşamalı tahmin yöntemi nedeniyle bu modelde bireysel serilerin GARCH süreciyle korelasyon süreci arasında ilişki yoktur. Ayrıca bu modelde bütün korelasyonların katsayılarının aynı olduğu varsayımı yapılmaktadır.

İki aşamalı tahminde, süreçler arasında bağlantı oluşturmak için Silvennoinen ve Terasvirta (2005) tarafından ortak hareketlerin incelenmesi için yumuşak geçişli koşullu korelasyon (Smooth Transition Conditional Correlation, STCC) modeli önerilmiştir. Bu modelde koşullu korelasyon için iki sabit korelasyon rejimi tanımlanmakta ve koşullu korelasyon geçiş değişkenin bir fonksiyonu olarak bu iki korelasyon rejimi arasında yumuşak olarak değişmektedir. Böylelikle STCC modeli finans piyasası katılımcılarının tamamının homojen olduğu ve karar ve tepkilerini aniden yaptığı varsayımı yerine rejimler arası yumuşak geçiş modelleyerek tepkilerin bireyden bireye değişebileceği, tepki zamanlama ve şiddetinin farklı olabileceği heterojen bir yapıya imkân vermektedir.

Bu çalışmada korelasyonların modellenmesinde sunduğu heterojen ve esnek yapı nedeniyle STCC-GARCH modeli ve genişletilmiş versiyonu olan "Double Smooth Transition Conditional Correlation" (DSTCC) modelleri kullanılmıştır. Çalışmamızda adı geçen tüm modellerin yapısı ve özellikleri ayrıntılı olarak tartışılmış, kestirim (estimation) yöntemleri basamak basamak ve test istatistikleri tüm detayı ve türetilmesi tüm aşamalarıyla ilk defa gösterilmiştir. STCC ve DSTCC modellerinin kestirimi ve test istatistiklerinin hesaplanması için hazır bir ekonometri programı bulunmamaktadır. Gerekli kodlar RATs.8 programında en esnek haliyle hazırlanmış ve kullanıma sunulmuştur. Literatürde STCC ve DSTCC modellerini kullanan çalışma sayısı çok sınırlıdır.

Bu çalışma kapsamında ilgilendiğimiz ve etkilerini test etmek istediğimiz değişkenlerin başında zaman değişkeninin kendisi gelmektedir. Bu değişken ile Türkiye ve Çin hisse senedi piyasaları ve tarımsal ürün ve değerli metal piyasaları ile gelişmiş hisse senedi piyasaları arasındaki korelasyonda artan bir trend olup olmadığını test edilmektedir. Türkiye ve Çin piyasaları için şimdiye kadar yapılan akademik çalışmaların hiç birinde artan trendin varlığını gösterebilecek bir delil bulunamamıştır.

Ayrıca korelasyonların küresel volatiliteden, piyasa volatilitesinden ve piyasalarından gelen iyi veya kötü haberden etkilenip etkilenmediği de korelasyonların yapısını ve özelliklerini ortaya çıkarabilmek için test edilmiştir.

Bulgular

STCC ve DSTCC modellerinin sahip olduğu esnek yapıyı kullanarak, bu tez çalışmamız Çin ve Türkiye hisse senedi piyasalarının ve iki emtia piyasasının (tarımsal ürün ve kıymetli metal) en kapsamlı ve güncel getiri korelasyon analizini üç bağımsız ve tam bölümde gerçekleştirmektedir. Bu analizler, bu kapsam ve esneklikte Çin ve Türk hisse senedi piyasaları ve emtia piyasaları için literatürde ilk kez yapılmaktadır.

Çin ve dört gelişmiş ülke (ABD, İngiltere, Fransa ve Japonya) hisse senedi piyasaları arasındaki getiri korelasyonları STCC-GARCH ve DSTCC-GARCH modelleri ile modellenmiştir. Yapılan analiz Çin hisse senedi piyasalarında işlem gören A tipi ve B tipi hisse senedi endekslerini kapsamaktadır. Öncelikle, STCC-GARCH modeli içinde zaman değişkenini geçiş değişkeni olarak kullanarak Çin finans piyasalarında gerçekleşen reformların bir sonucu olarak beklenen ama şimdiye kadar tespit edilememiş olan korelasyondaki artan eğilim için kanıt aranmaktadır. Sonra, küresel volatilitenin, endeksin öz volatilitesinin ve endekslerden gelen haberin yönünün koşullu korelasyon üzerindeki rolü STCC-GARCH ve DSTCC-GARCH modelleri kapsamında bu üç faktörün çeşitli ölçeklerini aday geçiş değişkeni olarak değerlendirerek incelenmiştir.

Mevcut literatürden farklı olarak, yükselen trendin varlığı tespit edilmiş ve sonuçlar A tipi hisse senedi endeksi ile S&P500, FTSE, CAC ve Nikkei endeksleri ve B tipi endeks ile S&P500 ve CAC endeksleri arasındaki korelasyonlarda artan trend olduğunu ortaya koymuştur. Beklendiği üzere, endeksler arasındaki korelasyonlarda artış eğiliminin başlangıç tarihi 2001-2006 yılları arasında Çin'de gerçekleşen mali reformların sonuç verdiği ve özellikle 2002 yılından sonra dünyanın geri kalanı ile Çin piyasalarının entegrasyonunun çok yol aldığı fikrini destekler nitelikte 2002 ve 2007 yılları arasında değişmekte ve dolayısıyla o tarihten itibaren portföy çeşitlendirme yöntemi ile elde edilecek yararları kısmen ortadan kaldırmaktadır. Yüksek seviyelere geçiş öncesinde koşullu korelasyonlar tüm endeks çiftleri için sıfıra çok yakındır. Ancak, 2007 yılından bu yana A tipi endeksin S&P500, FTSE, CAC ve Nikkei endeksleri ile olan koşullu korelasyonu sırasıyla ortalama olarak 0.21, 0.26, 0.298 ve 0.315 olarak gerçekleşmiştir. Diğer taraftan, B tipi endeks için, koşullu korelasyon S&P500 ile 0.6 ve CAC ile 0.5 seviyelerinin üstüne çıkarken FTSE ile 0.32 ve Nikkei ile 0.26 civarında kalmıştır.

Ayrıca, DSTCC-GARCH model sonuçları korelasyon yapısının piyasa volatilitesinden son derece etkilendiğini göstermektedir. A tipi endeksin gelişmiş endekslerle olan

korelasyonu volatilitenin yüksek olduğu dönemlerde sakin dönemlere kıyasla daha düşük seviyelerde olduğu tespit edilmiştir. A tipi endeksin S&P500, FTSE ve CAC endeksleri ile olan koşullu korelasyonu A tipi endeksin sakin dönemlerinde biraz daha artarak sırası ile 0.296, 0.337 ve 0.372 seviyelerine ulaşmaktadır. Benzer şekilde, küresel olarak sakin dönemlerde Nikkei ile korelasyon 0.621 seviyesine ulaşmaktadır. Diğer taraftan, B tipi endeks için ise karışık sonuçlar elde edilmiştir. B tipi endeksin gelişmiş endeksler ile olan korelasyonu S&P500, FTSE ve CAC endekslerindeki volatilitenin yüksek olduğu dönemlerde artmakta fakat küresel volatilitenin ve Nikkei endeksindeki oynaklığın artması ile azaldığı gözlemlenmiştir. Nikkei endeksinin sakin dönemlerinde B tipi endeks ile S&P500, FTSE ve CAC endeksleri arasındaki korelasyon sırası ile 0.841, 0.371 ve 0.373 ulaşmaktadır. Ancak bu korelasyon seviyeleri hala gelişmiş piyasalar arasındaki ve hatta gelişmiş ve bir çok gelişmekte olan piyasalar arasındaki korelasyon seviyelerine göre çok düşüktür. Dolayısıyla, Çin hisse senedi piyasaları, özellikle A tipi hisse senedi piyasası uluslararası yatırımcılara portföylerinin riskini azaltmak için değerli fırsatlar sunmaya devam etmektedir. Ayrıca, literatürde ilk kez, A tipi endeks ile S&P500 arasındaki korelasyonun korelasyon denklemlerinde varsayılan açıklayıcı değişken olarak kullanılan standardize edilmiş hata terimlerinin birinci gecikmesine verdiği tepkisinde yapısal bir değişim tespit edilmiştir. Bu bulgu koşullu korelasyonun sahip olduğu güçlü trend etkisi ile birlikte önceki literatürün kötü performansının sorumlusu olabilir.

Bir sonraki bölümde Türk hisse senedi piyasalarının uluslararası yatırımcılara portföy çeşitlendirmesi bağlamında fayda sağlayabilme potansiyelini değerlendirebilmek amacıyla Türkiye'deki ve dört gelişmiş ülkedeki (ABD, İngiltere, Fransa ve Almanya) hisse senedi piyasaları arasındaki koşullu korelasyonlar STCC ve DSTCC modelleri aracılığıyla modellenmiştir. Çin bölümünde olduğu gibi öncelikle koşullu korelasyon için artan trendin geçerliliği test edilmiş ve küresel volatilitenin, endekslerin öz volatilitesinin ve endekslerden gelen haberlerin koşullu korelasyon üzerindeki etkileri incelenmiştir. Ayrıca, Avrupa Birliğine 2004 ve 2007 yıllarında üye olan Macaristan, Çek Cumhuriyeti, Polonya, Bulgaristan ve Romanya hisse senedi piyasalarının ABD ve Almanya'daki hisse senedi piayasaları ile olan koşullu korelasyonları üyelik statüsünün korelasyon üzerindeki etkilerini test edilebilmek için STCC modeli kapsamında zaman değişkeninin geçiş değişkeni olarak kullanılmasıyla modellenmiştir. Birlik üyesi olmanın korelasyon üzerindeki etkilerini görebilmek için üyelik kabul tarihi koşullu korelasyonun düşük korelasyon seviyelerinden yüksek seviyelere geçmeye başladığı tarih ile karşılaştırılmıştır. Bu noktayı biraz daha açıklığa kavuşturmak için henüz üye olmayan Türkiye'deki ve Almanya'daki hisse senedi piyasaları arasındaki koşullu korelasyonun yukarı doğru eğiliminin zamanlaması yeni üyelerin hisse senedi piyasaları ile Alman hisse senedi piyasaları arasındaki korelasyonların artış zamanlaması ile karşılaştırılmıştır. Ayrıca, koşullu korelasyonların yüksek seviyelere geçişlerinde küresel faktörlerin mi yoksa AB ile ilgili gelişmelerin mi baskın

olduğunu konusu da ele alınmıştır. Bu amaçla, Türkiye ve yeni üyelerin hisse senedi piyasalarının Almanya hisse senedi piyasası ile olan koşullu korelasyonundaki artışın başlama tarihi ile Türkiye ve yeni üyelerin hisse senedi piyasalarının ABD hisse senedi piyasası ile olan koşullu korelasyonundaki artışın başlama tarihi ile mukayese edilmiştir. Artış AB ile ilgili gelişmelere bağlı ise tüm yeni üyelerin ve Türkiye'nin koşullu korelasyonlarının ABD den önce Almanya ile yüksek seviyelere çıkması beklenmektedir.

Zaman değişkeninin geçiş değişkeni olarak kullanıldığı STCC-GARCH modellerinin tahmin sonuçları Türkiye ile yeni üye ülkelerin hisse senedi piyasaları ile gelişmiş hisse senedi piyasaları arasındaki korelasyonların artış trendi içerdiğini göstermiştir. Yapılan mukayeseli analizler neticesinde korelasyonlardaki bu yükseliş trendinin üyelik statüsünden bağımsız olduğu ve artan trend üzerinde AB ile ilgili gelişmelerin önemli etkisi olmakla birlikte asıl olarak küresel gelişmelerin hakim olduğu sonucuna varılmıştır. 2005 yılından bu yana, ISX100 endeksinin S&P500, FTSE, CAC ve DAX endeksleri ile olan korelasyonları sırasıyla ortalama olarak 0.553, 0.656, 0.678 ve 0.661 düzeylerine yükselmiştir. Ayrıca, DSTCC-GARCH modellerinin tahmin sonuçları Türk hisse senedi piyasasının AB'deki gelişmiş borsaları ile olan koşullu korelasyonların Türk hisse senedi piyasa volatilitesinden yüksek oranda etkilendiğini göstermekte ve ISX100 endeksinin oynaklığının arttığı dönemlerde koşullu korelasyon daha da artarak DAX, CAC ve FTSE ile sırasıyla 0.799, 0.734 ve 0.8 seviyelerine ulaşmaktadır. Öte yandan, ABD hisse senedi piyasası ile korelasyon AB'deki gelişmiş ve ABD hisse senedi piyasalarının oynaklığından etkilenmektedir. Korelasyonların piyasa oynaklıklarına verdiği tepki 2003 yılı Ekim ayında değişmiştir. Bu tarihten önce koşullu korelasyon kargaşa dönemlerinde artma eğilimindeyken bu tarihten sonra kargaşa dönemlerinde düşüş eğilimine geçmiştir.

Özetlemek gerekirse, Türk hisse senedi piyasasının gelişmiş hisse senedi piyasaları ile olan korelasyonları Çin hisse senedi piyasalarının gelişmiş piyasalar ile olan korelasyonlarından önemli ölçüde yüksek olduğu ve dolayısıyla Çin hisse senedi piyasalarının portföy çeşitlendirmesi açısından karşılaştırmalı üstünlüğe sahip olduğu sonucu ortaya çıkmıştır.

Son olarak emtia piyasalarının finansallaşmasının bu piyasalar ile hisse senedi piyasaları arasındaki korelasyonlar üzerindeki olası etkilerini araştırmak için yatırım yapılabilir tarımsal ürün ve değerli metal endeksleri ile S&P500 endeksi arasındaki koşullu korelasyonlar dinamik koşullu korelasyon bağlamında STCC-GARCH ve DSTCC-GARCH modelleri ile formule edilmiştir. Benzer şekilde, bu bölümde de öncelikle artan trendin kanıtları aranmış ve korelasyonun özelliklerini ve yapısını açıklama yeteneğine sahip faktörler analiz edilmiştir. Tahmin sonuçları kıymetli metal ve S&P500 endeksleri arasındaki koşullu korelasyonda artan trendin varlığını ortaya çıkarmıştır. Koşullu korelasyon Ekim 2008 tarihinde yüksek korelasyon seviyesine

sıçramaktadır. Bu tarihten önce, korelasyon değerli metal endeksinin oynaklığına ve endeksten gelen habere göre -0.125 gibi düşük ve 0.116 gibi yüksek değerler almakta iken 2008 yılının son çeyreğinden itibaren, koşullu korelasyon portföy çeşitlendirme faydalarını önemli ölçüde bitirebilcek kadar yüksek (0.725) seviyelere ulaşabilmekte olduğu bulunmuştur.

Diğer taraftan, tarımsal ürün ve S&P500 endeksleri arasındaki korelasyonun ortalama değeri 2007 yılından bu yana artmasına rağmen bu deliller tarımsal ürün ve S&P500 endeksleri arasındaki korelasyonun emtia piyasalarının finansallaşması surecinde artan trend içerdiği sonucuna varabilmek için yetersizdir. Tahmin sonuçları korelasyondaki artışın yeni bir olgu olmadığını ve sadece son finansal krize isnat edilemeyeceğini ortaya çıkarmaktadır. 1999 yılından bu yana korelasyon tarımsal ürün ve S&P500 endekslerinin volatilitelerinin yüksek olduğu dönemlerde 0.6 mertebesine kadar yükselmektedir. Korelasyonun son birkaç yıldır yüksek seviyelerde olmasının sebebi her iki endeksin oynaklığının yüksek olması gibi görünmekte ve piyasaların yatışması durumunda düşük korelasyon seviyelerine geri dönebileceği ortaya konmuştur.

Sonuç olarak, bu tez çalışmamız Türkiye ve Çin hisse senedi piyasalarının ve tarımsal ürün ve değerli metal piyasalarının gelişmiş hisse senedi piyasaları ile olan korelasyonlarının yapısını ve özelliklerini incelemek için STCC-GARCH ve DSTCC-GARCH modellerinin ayrıntılı bir uygulamasını içermektedir. Sonuçlar oldukça umut verici ve piyasalar arasındaki hem yükselen korelasyonun varlığını hemde korelasyonların dinamik doğasının arkasındaki gerçekleri ortaya çıkarmaktadır. Sektörel düzeyde yapılacak olan korelasyon analizinin daha bilgilendirici olacağına ve değerli portföy çeşitlendirme stratejilerini ortaya çıkaracağına hiç şüphe yoktur. Ancak, ulusal hisse senedi piyasaları genelinde mevcut sektörel endekslerin farklı içeriklere sahip olması sektörel düzeyde endeksler arasındaki korelasyon çalışmasına engel oluşturmaktadır.

APPENDIX J
TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü ☐
Sosyal Bilimler Enstitüsü ☐
Uygulamalı Matematik Enstitüsü ☐
Enformatik Enstitüsü ☐
Deniz Bilimleri Enstitüsü ☐

YAZARIN

Soyadı : Öztek
Adı : Mehmet Fatih
Bölümü : İktisat

TEZİN ADI: Modeling Co-movements among Financial Markets: Applications of Multivariate Autoregressive Conditional Heteroscedasticity with Smooth Transition in Conditional Correlations

TEZİN TÜRÜ : Yüksek Lisans ☐ Doktora ☐

1. ☐ Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir.
2. ☐ Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir.
3. ☐ Tezimden bir bir (1) yıl süreyle fotokopi alınamaz.

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: