FUNDAÇÃO GETÚLIO VARGAS
ESCOLA DE ECONOMIA DE EMPRESAS DE SÃO PAULO

Maximilian-Benedikt Herwarth Detlef Köhn

Speculative bubbles and contagion: Analysis of volatility's clusters during the DotCom bubble based on the dynamic conditional correlation model

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Adviser:
Prof. Dr. Pedro Luiz Valls Pereira

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Prof. Dr. Afonso Fuzeta da Ponte da Cunha de Eça

Dedicated to the “Seven Fs”:

Faith, Family, Finances, Fitness, Friends, Fun and Future

by

Paul Batz (2011)

RESUMO

Revendo a definição e determinação de bolhas especulativas no contexto de contágio, este estudo analisa a bolha do DotCom nos mercados acionistas americanos e europeus usando o modelo de correlação condicional dinâmica (DCC) proposto por Engle e Sheppard (2001) como uma explicação econométrica e, por outro lado, as finanças comportamentais como uma explicação psicológica. Contágio é definido, neste contexto, como a quebra estatística nos DCC's estimados, medidos através das alterações das suas médias e medianas. Surpreendentemente, o contágio é menor durante bolhas de preços, sendo que o resultado principal indica a presença de contágio entre os diferentes índices dos dois continentes e demonstra a presença de alterações estruturais durante a crise financeira.

PALAVRAS CHAVE: bolha especulative, finanças comportamentais, contágio financeiro, DCC.

ABSTRACT

Reviewing the definition and measurement of speculative bubbles in context of contagion, this paper analyses the DotCom bubble in American and European equity markets using the dynamic conditional correlation (DCC) model proposed by Engle and Sheppard (2001) as an econometrical - and on the other hand the behavioral finance as an psychological explanation. Contagion is defined in this context as the statistical break in the computed DCCs as measured by the shifts in their means and medians. Even it is astonishing, that the contagion is lower during price bubbles, the main finding indicates the presence of contagion in the different indices among those two continents and proves the presence of structural changes during financial crisis.

KEY WORDS: speculative bubbles, behavioral finance, financial contagion, DCC.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike's Information Criterion
ARCH	Autoregressive Conditonal Heteroskedasticity
CCC	Constant Conditional Correlation
Coef.	Coefficient
Conf. Int.	Confidence Interval
DAX	Deutscher Aktienindex (German Stock Index)
DCC	Dynamic Conditional Correlation
e.g.	exempli gratia (for example)
et. al.	et alii (and others)
FPE	Final Prediction Error
FTSE100	Financial Times Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
HQIC	Hannan and Quinn Information Criterion
INDU	Dow Jones Industrial Average
IXIC	NASDAQ Composite
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
NASDAQ	National Association of Securities Dealers Automated Quotations
SBIC	Schwarz's Bayesian Information Criterion
SP500	Standard & Poor's 500
SXXE	EURO STOXX Index
Std. Err.	Standard Error
PP	Phillips-Perron
VCC	Varying Conditional Correlation

1. INTRODUCTION

The deviation of market prices from fundamental values is not only a phenomenon of the present, but is also observed since the last centuries, e.g.: The Tulipomania in Netherlands, the South Sea Bubble in Great Britain or even the DotCom bubble, see Carlos et al. (2006) or Ofek and Richardson (2003).

During those last centuries, the analysis of patterns of international spread of financial events became the subject of many academic studies. Especially, during price-bubbles, empirical research focused on volatility models and tried to answer the international markets' phenomena of high correlated markets.

De facto, financial markets around the world are getting more and more integrated. In those highly integrated markets any shock in a single market can quickly lead to a spill-over to other markets. The reason behind this can have different sources, for instance: financial, geopolitical, and political relations between those countries. Empirical studies of contagion events, which focus only on the fundamental relations among economies, are not able to explain satisfactorily those spillovers from one market to another. The behavioral finance theories offer a behavioral-psychological explanation for those different stock market anomalies and their spillover effects. Shock spillovers and thereby contagion can be attributed to irrational behavior of investors and for instance linked to a herding behavior among them, shown by Hirshleifer and Teoh (2009) and Ionescu et al. (2009).

The term contagion has been gone through a lot of different definitions and measurements, always trying to define and answer the process in a context of cross-country analysis. In the beginning, it was defined as a simple static measure of correlation between two market stock returns of two different countries, which identified and

transferred the relation to their respective equity markets and to a cross-country portfolio diversification, shown by Cho and Parhizgari (2008). Later on, researches – like Darbar and Deb (1997), Karolyi and Stulz (1996), and Parhizgari et al. (1994) – on correlation analyses tried to develop new measures and techniques by including co-movements, causality and error-correction models among cross-country market returns.

Meanwhile, like Forbes and Rigobon (2002) have shown, the estimation of correlations requires additional statistical refinements. Engle and Sheppard (2001) demonstrated that those estimations have to consider the dynamics - the time-varying and the constant - aspect of correlations, which is called dynamic conditional correlations (DCC).

In consideration of previous studies, this paper answers the following questions and closes thereby a rarely mentioned topic in the literature about the correlation of market indices and the evaluation of financial contagion between stock-market returns:

1. What is a speculative bubble and how can be indicated a typical price bubble?
2. Holds the - in many cases assumed - contagion effect between the American and European stock markets in the presence of price bubbles, like the DotCom bubble?
3. Which model is the best for analyzing the phenomenon of financial contagion between stock market returns of different countries?

In this context, the goals of this study are to analyze the DotCom price bubble as well to evaluate the financial contagion between American and European stock market returns in this context. Therefore, three multivariate conditional correlation volatility models will be used, the DCC-GARCH by Engle and Sheppard (2001), the constant conditional correlation (CCC) by Bollerslev (1990) and the varying conditional correla-

tion (VCC) by Tse and Tsui (2002). Nevertheless, the main focus lies on the DCC-GARCH model.

The paper is constructed as follows: Chapter 2 gives a short overview about the literatures of price bubbles and financial contagion. Chapter 3 defines generally price-bubbles and their development, subsequently the DotCom bubble is explained as well shortly analyzed. The chapter 4 starts with a short descriptive statistic of the considered data set and describes the empirical strategy according to test for financial contagion. Chapter 5 presents the results according to previous strategies and the last chapter concludes and compares the results with former findings.

2 OVERVIEW OF RELEVANT LITERATURE

According to the different parts of this study, the overview of relevant literature has to be split as well into two main parts: The first part deals with the definition of bubble and their different explanations. The second part deals about the contagion effect among the different indices.

2.1 PRICE BUBBLES

The discussion how to define and identify a bubble is not a new topic. Garber (2000) explains a bubble as “a fuzzy word filled with import but lacking any solid operational definition.” He defines both sides of a bubble, the positive as well as the negative. He suggests that a bubble can best be explained by “a price movement that is inexplicable based on fundamentals.” The main task of this definition is that a bubble can only be determined after it has been occurred, as O’Hara (2008) mentioned. For in-

stance, Kindleberger and Aliber (1996) defines that “a bubble is an upward price movement over an extended range that then implodes.” The most important assumptions to define a bubble are the irrationality versus the rationality. Arrow (1982) gives a short summary over the difference between individual rationality and irrationality and markets.

Blanchard and Watson (1982) published one of the first papers about bubbles in the financial markets regarding the rational expectations. The more recent paper by O’Hara (2008) summarized the overview of literature about bubbles in detail. In her paper, she distinguished different theories of bubbles. Therefore, she differentiated between rational and irrational traders, as well rational and irrational markets. Tirole (1982) and Brunnermeier and Nagel (2004) showed that a bubble could even occur under the assumption of rational investors and rational markets. The theory behind the irrationality of the markets is based on the theory of Kindleberger and Aliber (1996) and Keynes (1935). This paper analyzes the technology-bubble – often mentioned as the DotCom-bubble. Ofek and Richardson (2003) were one of the first authors, who explained the internet bubble in the 1990’s. Their conclusion is that the technology-bubble “burst to the unprecedented level of lockup expirations and insider selling”. This study assumes also rational markets, like Ross (2005) and Aschinger (1991) did. Garber (1990) gives a good overview over the past famous bubbles and concludes that a bubble is a present phenomenon and will occur frequently.

2.2 FINANCIAL CONTAGION

The literature about contagion effect in financial markets is that extensive to review here fully. The surveys from Kindleberger (1978), Kaminsky et al. (2003) and Bae

et al. (2003) are only some of those, which have to be mentioned. In general, the focus of most literatures is the contagion effect across countries. Therefore, the spread of crises from one country to another has been one of the most discussed issues in international finance since the last decades. This is caused by the frequently occurrence of the last crisis. Financial contagion characterizes situations in which local shocks are transmitted to others financial sectors or even countries. This is comparable with a pandemic, for instance an epidemic of infectious disease. One of the most known definition explains a contagion as a "structural change in the mechanism of the proliferation of shocks arising from a particular event or group of events associated with a particular financial crisis"; see Arruda and Pereira (2013). Applied to a financial crisis means this that a specific shock can propagate like a virus, starting in a country and overlapping even to other continents.

An interesting way to define contagion is the five-step definition by Pericolo and Sbracia (2001). According to the authors, contagion can be explained by a) an increased probability of a crisis in a country by a crisis in another - different - country; b) highly stock volatility as an uncertainty from crisis of a country to the financial market of another country; c) higher co-movements in stock prices or quantities between financial markets with and without crisis in the markets; d) difference in transmission mechanism or channel for contagion in and after the crisis; and e) co-movements which can not explained by the fundamentals.

For instance, Filleti et al. (2008) analyzed the contagion between the Latin American economies and two emerging markets. Armada et al. (2011) tested the contagion effect between the financial markets of nine developed countries and Azad (2009) for the Asian market. Horta et al. (2008) and as well Arruda and Pereira (2013) analyzed the

contagion effects during the US Subprime crisis. Marcal et al. (2011) evaluated the contagion in the financial crisis of Asia and Latin America.

Regarding to the technology-bubble, Anderson et al. (2010) studied the proliferation of the technology-bubble. Most of the studies applied variations of Engle and Sheppards' (2001) DCC model. Table 1 gives a short overview about the different researches, which mainly focus on the effect of financial crisis on emerging markets.

Empirical researches for financial contagion or volatility spillover effects using Multivariate GARCH models

Author(s)	Year	Model	Specific topic
Chiang, Jeon and Li	2007	DCC 8 Asian EMs	Financial crisis in Asia in 1997, the effect of credit-rating agencies on the structure of correlation dynamic.
Kuper and Lestano	2007	DCC 6 Asian EMs	Effect of financial crisis on the interdependence of financial and FX markets
Cheung, Fung and Tan	2008	DCC 11 EMEAP and US	Interdependence of financial markets. Contagion risk of in EMEAP region
Cho and Parhizgari	2008	DCC 8 Asian EMs	East Asian financial contagion under DCC-GARCH
Beirne, Caporale, Ghatlas, Spagnolo	2009	MGARCH-in-mean 41 EMs: Asia, Latin America, Middle East	Global and Regional volatility spillover
Frank, Gonzalez-Hermosillo and Hesse	2009	DCC, GARCH US: LIBOR, S&P500, ABCP	Transmission of Liquidity Shocks: Evidence from the 2007 Subprime Crisis
Munoz, Marquez and Chulia	2010	TSCA, DCC 19 EMs: North America, Europe, Asia	Asian financial crisis, Dot-com crisis, Global financial crisis
Yin, Ho and Choi	2010	PCA, ADCC 11 EMEAP and US	Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil
Naoui, Khemiri and Limame	2010	DCC 10 EMs: Asia, Latin America and US	Sub-prime crisis 2007
Kenourgios, Samitas and Paltalidis	2011	AG-DCC, capula-DCC BRIC, UK, US	Five recent financial crises
Marcal, Valls Pereira, Martin and Nakamura	2011	DCC 9EMs: Argentina, Brazil, South Korea, US, Singapore, Malaysia, Mexico and Japan	Evaluation of contagion or interdependence in the financial crisis of Asia and Latin America, considering the macroeconomic fundamentals
Kazi, Guesmi and Kaabia	2011	DCC 17EMs: OECD countries	Contagion Effect of Financial Crisis on OECD Stock Markets
Celik	2012	DCC GARCH 8 EMs: Japan, Malaysia, Denmark, India, Canada, China, Australia, Brazil	The more contagion effect on emerging markets: The evidence of DCC-GARCH model
Chittedi	2015	DCC GARCH India and US	Financial Crisis and Contagion Effects in Indian Stock Market: DCC -GARCH Analysis

TABLE 1: OVERVIEW OF EMPIRICAL RESEARCHES

None of the previous studies analyzed only the contagion effect between American and European indices during the technology-bubble, most of the studies related the contagion between developing, industrialized and emerging countries.

Consequently, this paper will confirm the hypothesis of financial contagion during the technology-bubble, if structural breaks are identified. In contrast to previous papers, like Anderson et al. (2010), Koller et al. (2010), Phylaktis and Xia (2006),

which analyzed the financial contagion among several industry-sectors in a specific country, this paper will focus on the contagion within different countries during the technology-bubble. The presence of a contagion effect can be determined by the increase in conditional correlations of the indices during the period of crisis compared to the previous periods.

3 PRICE-BUBBLES AND THEIR IDENTIFICATION

"A market in which prices always fully reflect available information is called efficient", by Fama (1970)

3.1 INTRODUCTION AND DEFINITION

As mentioned before, many papers focus on the explication, proof and analysis of market mispricing. Particularly, many well-known scientists - leading by Shiller (2000) and Fama (1965) - are engaged in the detection of bubbles. There are different opinions how to define a price-bubble. There are two kinds of bubbles: The deterministic bubble, which will burst in a specific time or the stochastic, which will increase to infinite, as seen in figure 1. Trivially said and knew from the efficient-market hypothesis of Fama (1970): An investor cannot score abnormal returns, because all relevant and available information are included in stock prices.

Nevertheless, at the beginning of every speculative price-bubble there is a belief of high probability of excess returns, see therefore Garber (1990). In an efficient market, stock-market changes are only justified with new information. During the development of a speculative bubble the investor knows that the prices are over-valuated. Even

normally no new information are published, which could explain those high stock-prices.

Notwithstanding, one of the most-known definitions is following: A positive price-bubble is the deviation of market price from the expected discounted dividends (this is called the fundamental value) and is based on the dividend model of William (1938):

$$P_t > \sum_{t=1}^{\infty} \frac{E(D_t)}{(1+\mu)^{t-1}} \quad (1)$$

P_o defines market price, D_t dividends and μ returns. Speculative bubbles can arise from stock's price-expectation. As mentioned before, there are two types of bubbles. The main focus of this paper, as those of Scherbina (2013), Jarchow (1997), will be stochastic bubbles. Those can burst with a specific probability during the time-period. In contrast to stochastic bubbles, deterministic bubbles increase to infinite. If a bubble burst, there are two following opportunities:

1) The market price will fall behind in the fundamental value, or

2) the market price will fall below the fundamental value.

Figure 1**,** based on the theory of Aschinger (1991) and Jarchow (1997), shows the different two scenarios: a deterministic B^{det} and a stochastic bubble (B^{stoch}) under the assumption that the fundamental value stays constant during time.

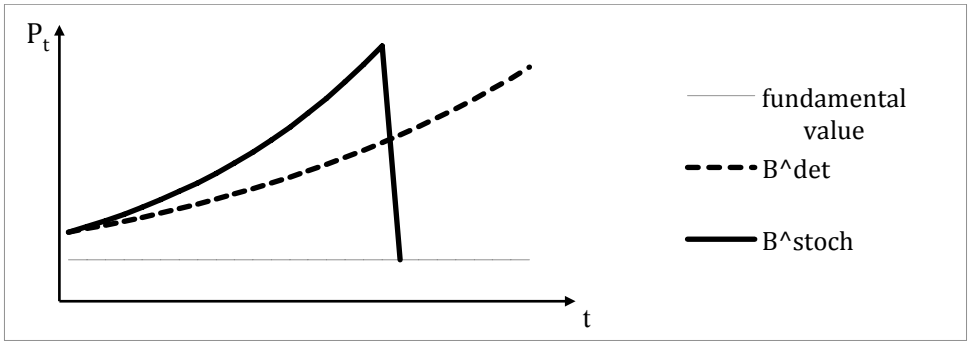

FIGURE 1. STOCHASTIC AND DETERMINISTIC BUBBLES

3.2 TYPICAL DEVELOPMENTS OF BUBBLES

The majority opinion about a typically development of a bubble is based on Kindleberger and Aliber (2005), Rosser et al. (2012) and Aschinger (1991). Below, the characteristics and phases of a speculative bubble are illustrated generally - as well - compared to the technology-bubble:

1) The beginning of each bubble is initiated with an exogenous shock, which implicates pervasive economical changes. In this phase a full branch of an industry can be changed. The exogenous shock can be caused by economical or political reasons; some are even caused by new technological developments. Structural changes raise the optimism of investors, banks and companies. The optimism and the expectation of a new welfare and new expected profit of the companies encourages investments to risky stocks. The expectation of stock market is positive. Therefore, investors hope for higher returns than in status quo ante.

2) The next step of a speculative bubble - the *boom* - is reached by the expectation of always continuing raising returns and a potential new market. By dint of equation 1 means that, that the market price is now a multiple of its proper fundamental value.

3) In consequence to the phase of the *boom,* interest rates are generally reduced, credit activities are increased and therefore, the total money supply increases. This behavior intensifies the proper *boom*-phase. The demand for credit increases permanently.

4) The abnormal increase of the stocks allures speculators and the credit activities are expanded by lower interest rates. A perpetual growing spectrum of participants from wealthy investors, debt-financed investors, and in the end speculators characterizes the climax of each bubble, the *euphoria*.

5) A disproportionately high return-expectation arouses even more investors, who are investing even more capital in the price-bubble. In this phase behavioral and irrational factors determine the investors' buying behavior. For instance, *bandwagon effects* are incorporated into behavioral effects: Following the motto, if others are buying, I will also buy. Those herd instincts happen avalanche-like and increase the capital inflow of each bubble, as Weil (2010) showed.

6) Due to higher interest rates, stagnant price trends or rejection of new technologies- the expectation can dramatically change. The first disembark of insiders, who would like to liquidate their winnings, triggers speculations of declining stock prices.

7) Professional investors escape. The others, the much bigger mass of non-professional investors, are trying to liquidate their winnings as well. This will lead to a huge increase of the demand of liquids funds in fear of illiquidity. The mass gets into a kind of a panic and sells their stocks at any price. Because the order of selling dominates, the prices will decline strongly. The speculative bubble burns, and the prices will go back to their fundamental value. This is caused to the microeconomic model supply and demand; stock prices will decrease at oversupply.

3.3 TECHNOLOGY-BUBBLE AND THEIR DEVELOPMENT

The following chapter will give a short overview about the technology-bubble – also called DotCom bubble because of the domain ending COM – and analyze it with the help of the previous shown development.

The technology-bubble started not at a fix time, it grew during the early 90's caused to a new technology-era- the Internet sector and it's associated industry sectors.

The start of the technology-bubble was caused by the hope, that the internet can improve the productivity of a company and therefore increase their expected profits.
As Xiong (2013) and Scherbina (2012) have shown the interest of achieving excess returns grew in times of the technology boom, especially of private investors.

The chart of the index NASDAQ gives a good overview of this speculative bubble: The NASDAQ increased since the end of the 90's. It doubled up in the time period between 1996 and 1998 and even quadrupled in the time between 1998 and 2000. Especially during the technology-bubble, the demand of internet-companies was enormous, whereupon the expected profit, respectively the winning-probability, of those companies were excluded and evaluated even illusory. The basic idea behind the trade of those stocks was trivially: One thought that the companies would offer their services for free at the beginning, thus would improve their market share and would generate some sales at a future date. Many of those new founded companies had the same business-idea and competed against each other. The technology-bubble burst in March 2000. Analog to the foundation of many new companies with similar business-ideas and their parallel increase in stock-prices, many of those companies moved avalanche-like - as well - to the other direction up to bankruptcy in March 2000. Discussed by Scherbina (2012), Ofek and Richardson (2003), Xiong (2013) and Brunnermeier and Nagel (2004) as well. Figure 2 shows on the left hand the NASDAQ Composite (IXIC) as well on the right hand the compounded NASDAQ Composite. Those figures illustrate exemplary the typical trend of a speculative bubble with their high volatility around the peak.

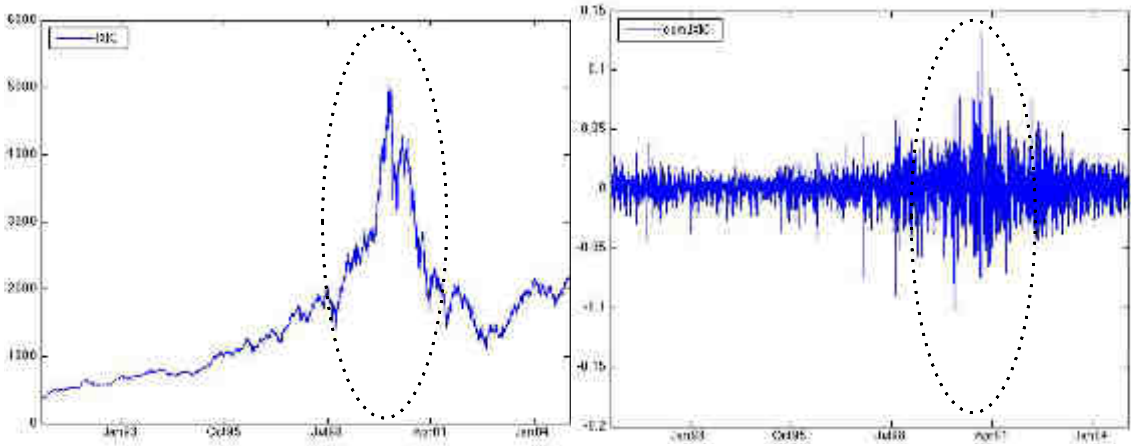

FIGURE 2. NASDAQ COMPOSITE AND COMPOUNDED NASDAQ COMPOSITE 1990 - 2005

The technology-bubble triggered an enormous worldwide financial crisis and showed the influences of overoptimistic perspectives for the Internet industry and therefore, the high stock prices. Figure 3 shows the INDU, DAX, FTSE100, SP500, SXXE, and IXIC. The graph shows the series with all indices normalized to 100 points on the first day of the sample, 1 December 1990. The indices are normalized to illustrate better the relative performance of the initial value of each index.

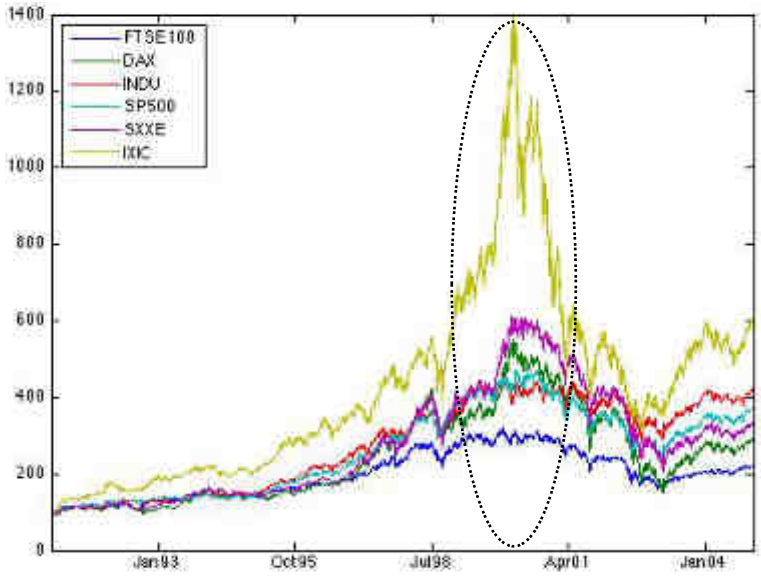

FIGURE 3. AMERICAN AND EUROPEAN INDICES 1990-2005

As one can see, all graphs have a similar trend and the series are not stationary. The peak of the technology bubble was in March 2000, but the impact of the technology

bubble is different. For instance, some markets are highly volatile, like IXIC or SXXE, others like FTSE100 shows a more stationary trend behavior.
Nevertheless, one can identify some volatility cluster and show that this holds even for the compounded returns - as will be shown later on in chapter 4.

3.4 BEHAVIORAL FINANCE

A main important part of the puzzle of a speculative bubble is the assumption of a Homo Oeconomicus, a fully rational individual. But especially individuals, like investors, tend to overreact or make decision regarding irrelevant information's. This is in contrast to the assumption of a full-rational investor, who will always make rational, utility-maximizing decisions, like Sheffrin (1983) and Simon (1979) point out. This irrational behavior tends to result in excess volatility clusters. Therefore, to understand more in detail which physiological factors drive a bubble, this chapter will focus on the behavioral finance and analyze those with the dotcom-bubble. The behavioral finance is a new behavioral-scientific approach, which explains stock volatilities during speculative bubbles with the help of psychologies and rational models. Employing behavioral-scientific approaches, the processing of relevant information's are analyzed to explain speculative bubbles. (Nguyen and Schueßler 2011)

3.4.1 FEEDBACK TRADING MODEL

One of the main discussed models of the behavioral finance is the *Feedback Trading model* at the stock market. This model produces a speculative bubble under the assumption that the stock demand of an investor's group is based only on historical

trading information's. The mechanism of those models allows a bubble to grow with more capital inflow until a certain time. At the moment when the capital inflow will rapidly decrease, the bubble will break down.

The following example will explain this theory:

Caused by positive news of a company their stock price increases. Some investor groups buy those stocks with the expectation that the stocks will increase in the future and therefore, the return increases as well. The first step is to define the trading volume as the amount of trading stocks of those companies. The demand after those stocks increases with the expectation of growing returns and involving that the stock price will be higher than the fundamental value. The trading volume increases also because of the amount of money. Those will attract as well other *Feedback Traders*, who are expecting that the price will still grow. This schematic repeats as long as no capital is invested anymore. At this point, the price will not grow anymore. Investors would like to sell their stocks profitably. The necessary demand of capital threatens the bubble- it can and will burst, see Scherbina (2013) for more details.

A bubble will burst therefore, when the supply of capital is exhausted. To grow a speculative bubble need to get more new invested capital. Once the capital inflow will decrease, the prices will fluctuate. The result of this will change the optimistic mood, which will deflate the bubble as well. In fact, there are some indicators that a bubble will burst as soon as a huge amount of unprofessional investors are speculating with those overpriced stocks, as Scherbina (2013) showed.

Many behavioral models assume that competitive arbitragers limit the huge price volatilities. The following model by De Long et al. (1990a) shows that rational arbitragers intensify more than dissolve the price volatilities under certain circumstances. The

model implies three investor types, based on DeLong et al. (1990a) and Scherbina and Schlusche (2012):

1) *Positive Feedback Trader*: The base of the stock demand is based only on past prices changes.

2) *Passive Trader*: The trading base is dependent on the asset value relative to their fundamental value.

3) *Informed rational speculators*: The foundations of their trading's are news about the fundamental value as a hypothesis for future price movements.

With the help of those models Belhoula and Naoui (2011) showed that rational investors tend to destabilize than to stabilize stock prices. One assumption is that the rational investors know the *Feedback Traders* based their future demand on the base of past price changes. To get higher price volatility, speculators have a higher demand of trading than in absence of *Feedback Trader*. If *Feedback Traders* entrance the market, the speculators invert their trading's and earn the profit from the *Feedback Trader*'s expense.

The model shows clearly that rational speculators are not trading against expected future mispricing's, which occurs as a result of an overreaction of the *Feedback Traders* to past prices changes. Instead, rational speculators anticipate the behavior of *positive Feedback Traders* and drift the prices up. In following rational trader will gain from those mispricing's and buy the stocks to sell those later to inflationary prices. The rational arbitragers will benefit from the bandwagon effect instead of trading against the mispricing's. All in all, a bubble arises from those rational, speculative behaviors. Those findings coincide with the conclusions of Abreu and Brunnermeier (2003) and DeLong et al. (1990b).

3.4.2 OTHER BEVAVIORAL EXPLANATIONS

This following section will discuss some more behavioral aspects to understand better the behavioral explanation of a speculative bubble. *Overconfidence* and *over optimism* are important for the evaluation of stock prices, as De Bondt (1998) found out. Individuals tend to be overoptimistic if they have an own influence on stock prices. The phenomenon of *overconfidence* explains that every individual has a higher confidence in his own expectation and evaluation. Both phenomena's are documented by experiments: Stocks, which are held in their own portfolios, are getting overvaulted belong their returns and expected growth.

Another effect is called the *bandwagon effect* or as well the *herding behavior*, based on DeBondt and Forbes (1999). This phenomenon explains the buying behavior, which is influenced by the buying behaviors of others. This means: A non-professional investor buys/sells stocks analog to the market/investors-majority in a speculative bubble. He makes his decision based on other market participants, which emblematize the majority. This behavior is relevant: On the right hand, he does not deviate from the majority opinion, because the majority cannot be wrong. On the other hand, he is not willing to swim against the stream and be against the majority. Nguyen and Schueßler (2011) analyzed this specific behavior.

Another aspect that occurs during a bubble is the *Narrow Framing*, researched and introduced by Barberis and Thaler (2002) and Barberis et al. (2006). This means that individuals judge differently over identical stocks in the same decision situations, if the stock or portfolio strategy is positive described. In the initial stage of the technology-bubble one assumed a huge benefit of new technology innovations. In those times stocks of companies, which expected an extensive excess profit regarding to the new

technologies, get an even higher rating than if they were objective rated. Non-professional investors tends also to hold bad-performed stocks to long, so that, they do not have to realize their loses. That loss-aversion affects the behaviorism of each investor.

To understand the formation phase of a speculative bubble you have to take those previous behaviors in consideration. Under rational assumption, it does not make sense to invest in stocks, which have a higher market value than their fundamental value. But this happens explicit during bubbles as shown by Weil (2010) and as well by Nguyen and Schueßler (2011). Non-rational investing means not only that stock prices are determined not always objective by future expectations but also biased by individual characters and their emotional factors, as respectively shown by the studies of Barberis et al. (2006), Kugler and Hanusch (1992).

4 METHODOLOGY AND EMPIRICAL SPECIFICATION

In following chapter, the data set will be analyzed as well as the dynamic conditional correlation (DCC) model will be explained.

4.1 DATA

The data on stock market prices consists of the Standard and Poor's 500 (SP500), Dow Jones Industrial Average (INDU), NASDAQ Composite (IXIC), Financial Times Stock Exchange (FTSE100), Deutscher Aktienindex (DAX) and Euro STOXX Index (SXXE) for U.S., U.K. and Germany. (All indices are shown in figure 6 in the appendix.) The reason for choosing this group of countries is the idea of having three repre-

sentatives for American and as well three for European markets. The daily data are collected over the period from December 1, 1990 to December 31, 2014.

All data are obtained from Bloomberg. Daily data are used in order to retain a high number of observations to adequately capture the rapidity and intensity of the dynamic interactions between markets.

Figure 4 presents the normalized stock market indices with an interesting pattern. Using normalized stock market prices; the figure illustrates better the relative performance of the initial value of each index than plotting all indices naturally, as seen in Figure 5 in the Appendix. Figure 4 identifies a period of joint fall in all the indices concentrated during the highlighted period (from July of 1998 to October of 2001).

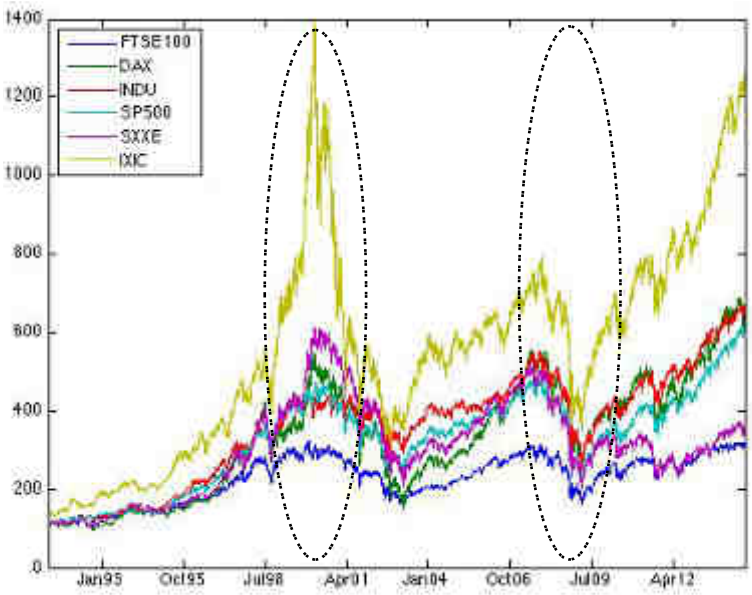

FIGURE 4. NORMALIZED STOCK MARKET INDICES

Regarding the sample definition, the intention was to select an extensive set of historical data with approximately a 24-year period, which amounted to 5952 observations for each series. Compounded market returns *i* (index *i*) at time *t* are computed as following:

$$r_{i,t} = \log(\frac{P_{i,t}}{P_{i,t-1}}), \quad (2)$$

where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices for day t and $t-1$, respectively. Figure 7 indicates those compounded market returns and identifies some clusters, especially in times of crisis and bubbles. As Figure 7 clearly shows, the volatility cluster during the DotCom period seems to be more sprawled than the subprime crisis, which had highly returns in a short-term.

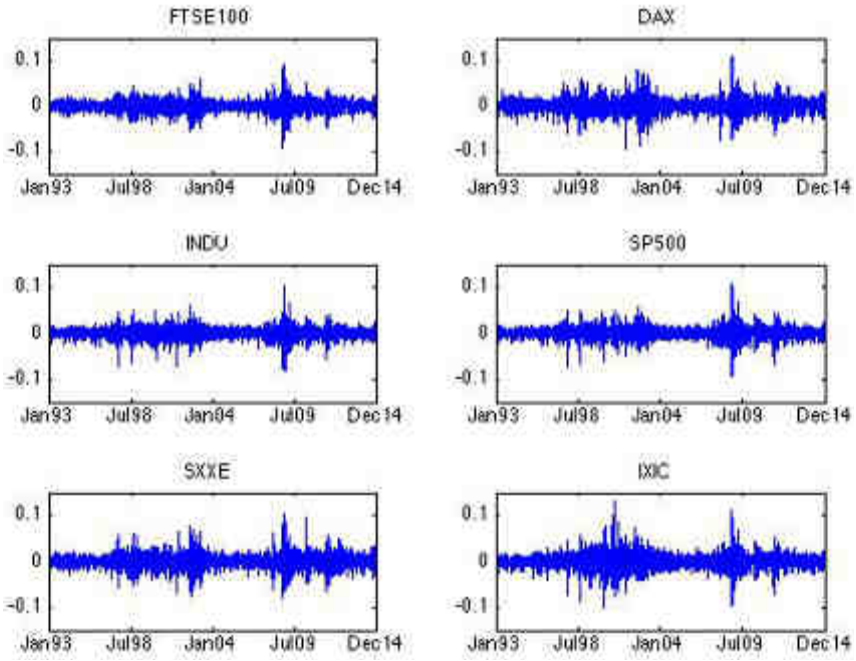

FIGURE 7. STOCK MARKET RETURNS

4.2 DESCRIPTIVE STATISTICS

The descriptive statistics of the data are given in table 2, which is divided in two panels A and B. As seen from panel A, the mean value for each return series is close to zero and for each return series the standard deviations are larger than the mean values and varies from 1.05% to 1.45%. The minimum alters from -8.20% to -10.17% and the maximum varies from 9.38% to 13.26%. Each compounded market return displays a small negative amount of skewness and large amount of kurtosis - varies between 8.06

to 11.78 - indicating that there are bigger tails than the normal distribution and therefore, the returns are not normally distributed.

In panel B, unconditional correlation coefficients in stock market index returns indicate strong pairwise correlations. The correlations within the different continents are highly positive over the full sample. The European indices: FTSE100, DAX and SXXE, have a correlation between 76% to 90% and the American Indices: INDU, SP500 and IXIC, have nearly 78% to 96%. The correlations between the different continents are even high; every correlation is bigger than 44%. Those high positive unconditional correlations are the first indicators for a strong contagion effect.

Descriptive statistic of compounded stock market returns

Panel A: Descriptive statistic							
	Mean	Min	Max	Std.dev.	Kurtosis	Skewness	Jarque-Bera
FTSE100	0.00019	-0.09265	0.09384	0.01133	9.10535	-0.07465	9248.26
DAX	0.00032	-0.09871	0.10797	0.01454	8.06284	-0.11492	6368.85
INDU	0.00033	-0.08201	0.10508	0.01098	11.34602	-0.15072	17294.31
SP500	0.00031	-0.09470	0.10957	0.01157	11.77817	-0.24339	19165.48
SXXE	0.00021	-0.08208	0.10438	0.01385	8.23300	-0.06048	6793.79
IXIC	0.00043	-0.10168	0.13255	0.01522	9.01064	-0.08929	8966.10

Panel B: Summary of unconditional correlation matrix of compounded stock market returns						
Full sample						
	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1.00000	0.75810	0.50847	0.51457	0.83884	0.44186
DAX		1.00000	0.55048	0.55373	0.90782	0.50494
INDU			1.00000	0.96170	0.54172	0.78351
SP500				1.00000	0.54935	0.87168
SXXE					1.00000	0.48908
IXIC						1.00000
Dot-Com - 1990-2005						
	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1.00000	0.67992	0.42409	0.43012	0.78959	0.36347
DAX		1.00000	0.48555	0.49270	0.87797	0.44362
INDU			1.00000	0.94085	0.46156	0.69273
SP500				1.00000	0.47211	0.82992
SXXE					1.00000	0.42078
IXIC						1.00000

TABLE 2. DESCRIPTIVE STATISTICS OF COMPOUNDED STOCK MARKET RETURNS

The results of the unit root tests for the market returns are summarized in table 3. The Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests are used to explore the existence of unit roots in individual series. The results of unit root tests have rejected the null hypothesis of the unit root for all market returns, indicating that the return series are trend stationary.

Unit root tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS)

Stock market returns						
	ADF statistics				PP statistics	KPSS statistics
	None	Constant	Time Trend	Constant and time trend		
FTSE100	-34.660	-34.695	-34.746	-34.730	-78.060	0.049
DAX	-77.373	-77.405	-77.413	-77.418	-77.386	0.062
INDU	-58.259	-58.338	-58.363	-58.358	-81.073	0.073
SP500	-58.727	-58.793	-58.814	-58.813	-81.931	0.094
SXXE	-36.975	-37.000	-37.061	-37.032	-78.214	0.064
IXIC	-57.165	-57.231	-57.255	-57.251	-77.670	0.113

TABLE 3. UNIT ROOT TESTS: ADF, PP AND KPSS

Figure 8 depicts the plots between every indices. Visually, one can see a higher relationship between indices from the same continent, for instance SP500 and INDU, or DAX and SXXE. It is not a perfect relationship, because not all points are lying exactly on the straight lines. The closer they are to the line (taken altogether), the stronger would be the relationship between the variables. These relationships between the series are linearly fitted by straight red lines.

4.3 MODEL SPECIFICATIONS

The econometric method is based on the modeling of multivariate time-varying volatilities. One of widely used models is DCC one of Engle and Sheppard (2001) and Tse and Tsui (2002), which captures the dynamic of time-varying conditional correlations, contrary to the benchmark CCC model by Bollerslev (1990) which keeps the conditional correlation constant. The main idea of this models is that the covariance trix, H_t, can be decomposed into conditional standard deviations, D_t, and a correlation matrix, R_t. D_t as well R_t are designed to be time-varying in the DCC GARCH model.

The specification of the DCC model can be explained as follows:

$$r_t = \mu + \sum_{s=1}^{p} \phi_s r_{t-s} + \varepsilon_t \ \ for\ t = 1, \dots, T\ and\ \varepsilon_t | \Omega_{t-1} \sim N(0, H_t), \qquad (3)$$

where r_t is a 6×1 vector of stock market index returns.

The error term, ε_t, from the mean equations of stock market indices can be presented as

follows with z is a 6×1 vector of i.i.d errors:

$$\varepsilon_t = \left(\varepsilon_{FTSE100,t}, \varepsilon_{DAX,t}, \varepsilon_{INDU,t}, \varepsilon_{SP500,t}, \varepsilon_{SXXE,t}, \varepsilon_{IXIC,t}\right)' = H_t^{\frac{1}{2}} z_t \tag{4}$$

$$with\ z_t \sim N(0, I_6).$$

H_t is the conditional covariance matrix and is given by following equation:

$$H_t = E(\varepsilon_t \varepsilon_t' | \Omega_{t-1}). \tag{5}$$

Therefore, equation can be written for the 6 different market indices:

$$\begin{bmatrix} r_{FTSE100,t} \\ r_{DAX,t} \\ r_{INDU,t} \\ r_{SP500,t} \\ r_{SXXE,t} \\ r_{IXIC,t} \end{bmatrix} = \begin{bmatrix} \mu_{FTSE100} \\ \mu_{DAX} \\ \mu_{INDU} \\ \mu_{SP500} \\ \mu_{SXXE} \\ \mu_{IXIC} \end{bmatrix} + \sum_{s=1}^{p} \begin{bmatrix} \phi_{11}^s \phi_{12}^s \phi_{13}^s \phi_{14}^s \phi_{15}^s \phi_{16}^s \\ \phi_{21}^s \phi_{22}^s \phi_{23}^s \phi_{24}^s \phi_{25}^s \phi_{26}^s \\ \phi_{31}^s \phi_{32}^s \phi_{33}^s \phi_{34}^s \phi_{35}^s \phi_{36}^s \\ \phi_{41}^s \phi_{42}^s \phi_{43}^s \phi_{44}^s \phi_{45}^s \phi_{46}^s \\ \phi_{51}^s \phi_{52}^s \phi_{53}^s \phi_{54}^s \phi_{55}^s \phi_{56}^s \\ \phi_{61}^s \phi_{62}^s \phi_{63}^s \phi_{64}^s \phi_{65}^s \phi_{66}^s \end{bmatrix} \begin{bmatrix} r_{FTSE100,t-s} \\ r_{DAX,t-s} \\ r_{INDU,t-s} \\ r_{SP500,t-s} \\ r_{SXXE,t-s} \\ r_{IXIC,t-s} \end{bmatrix} + \begin{bmatrix} \varepsilon_{FTSE100,t} \\ \varepsilon_{DAX,t} \\ \varepsilon_{INDU,t} \\ \varepsilon_{SP500,t} \\ \varepsilon_{SXXE,t} \\ \varepsilon_{IXIC,t} \end{bmatrix}. \tag{6}$$

Applying Engle and Sheppards's 2001 dynamic conditional correlation model, the $r_t = \left(r_{FTSE100,t}, r_{DAX,t}, r_{INDU,t}, r_{SP500,t}, r_{SXXE,t}, r_{IXIC,t}\right)'$ is a 6×1 vector of stock market returns, such that $r_{FTSE100}$ is the return of FTSE 100, respectively the other indices with $r_t | \Omega_{t-1} \sim N(0, H_t)$.

The conditional covariance matrix H_t is defined by two components on the CCC model, which are estimated independent of each other: The sample correlations H_t and the diagonal matrix of time varying volatilities D_t. Therefore, the covariance forecast is given by following equations:

$$H_t = D_t R_t D_t, \tag{7}$$

where $D_t = diag\left(\sqrt{h_{FTSE100,t}}, \sqrt{h_{DAX,t}}, \sqrt{h_{INDU,t}}, \sqrt{h_{SP500,t}}, \sqrt{h_{SXXE,t}}, \sqrt{h_{IXIC,t}}\right)$ is a 6×6 diagonal matrix of time varying standard deviations from the univariate GARCH models, for

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{8}$$

$for\ i = FTSE100, DAX, INDU, SP500, SXXE, IXIX$ and the time varying conditional

correlation matric is defined by:

$$R_t = \{\rho_{i,t}\}. \tag{9}$$

Getting the DCC-GARCH model, two steps have to be taken. The first one is to estimate a univariate GARCH model. The second stage is to define the vector of standardized residuals, $\eta_{i,t} = \frac{r_{i,t}}{\sqrt{h_{i,t}}}$ to develop the DCC correlation specification:

$$R_t = diag\left(q_{11}^{-\frac{1}{2}}, \dots, q_{66}^{-\frac{1}{2}}\right) Q_t \; diag\left(q_{11}^{-\frac{1}{2}}, \dots, q_{66}^{-\frac{1}{2}}\right), \tag{10}$$

where $Q_t = (q_{i,j,t})$ is a symmetric - positive defined - matrix. Q_t varies according to a GARCH-type process as follows:

$$Q_t = (1 - \theta_1 - \theta_2)\tilde{Q} + \theta_1 \eta_{t-1}\eta'_{t-1} + \theta_2 Q_{t-1} \tag{11}$$

The variables, θ_1 and θ_2, are positive, $\theta_1 \geq 0 \; and \; \theta_2 \geq 0$ and, therefore, $\theta_1 + \theta_2 < 1$. $\theta_1 \; and \; \theta_2$ define scalar parameters, which capture the effects of previous shocks and previous dynamic conditional correlation on current dynamic conditional correlation. $\tilde{Q}$ explains the 6×6 unconditional variance matrix of all standardized residuals $\eta_{i,t}$ with a correlation estimation like following:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\, q_{j,j,t}}} \leq 1 \tag{12}$$

As Aielli (2013) pointed out in the DCC model the choice of $\tilde{Q}$ is not obvious as Q_t is neither a conditional variance nor correlation, even $E(\eta_{t-1}\eta'_{t-1})$ seems to be inconsistent for the target because of Q_t not having a martingale representation. Aielli (2013) solved the issue of the lack of consistency and the existence of biased estimation parameters by introducing a corrected DCC model (cDCC). This model has nearly the same specification as Engel's (2002) DCC model, except the correlation Q_t:

$$Q_t = (1 - \theta_1 - \theta_2)\tilde{Q} + \theta_1 \eta^*_{t-1} {\eta^*}'_{t-1} + \theta_2 Q_{t-1}, with \; \eta^* = diag(Q_t)^{\frac{1}{2}} \eta_t \tag{13}$$

5 EMPIRICAL RESULTS

Table 4 reports the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC) lag order selection statistics for a series of vector auto-regressions of order 1 through a requested maximum lag. The equation for the FPE is given by Luetkepohl (2005), with T as the number of observations and K as the number of equations:

$$FPE = |\Sigma_u| \left(\frac{T+Kp+1}{T-Kp-1}\right)^K \tag{14}$$

AIC, SBIC and HQIC are computed according to their standard definitions, see fore those equations Akaike (1974), Schwarz (1978) and Hannan and Quinn (1979):

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T} \tag{15}$$

$$SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T} t_p \tag{16}$$

$$HQIC = -2\left(\frac{LL}{T}\right) + \frac{2\ln(\ln(T))}{T} t_p, \tag{17}$$

where LL is the log likelihood and t_p indicates the total amount of parameters in the model.

Table 4 is the result as preestimation. This preestimation version is later used to select the lag order for the three different MGARCH-models.

Selection-order criteria
Sample: 5 - 5951 Number of obs: 5947

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	127377.0				1.00E-26	-42.8352	-42.8329	-42.8285
1	128188.0	1622.9	36	0	7.54E-27*	-43.1318*	-43.0796	-43.0488*
2	128289.0	202.96	36	0	7.60E-27	-43.1180	-43.0875*	-43.0303
3	128367.0	154.16	36	0	7.55E-28	-43.0960	-43.0873	-43.0303
4	128397.0	60.263*	36	0.007	7.56E-28	-43.1299	-43.0712	-42.9611

Endogenous: FTSE100 DAX INDU SP500 SXXE IXIC
Exogenous: _cons

TABLE 4. OBTAIN LAG-ORDER SELECTION STATISTICS

The "*" indicates the optimal lag. Even, the FPE is not an information criterion; the prediction error has to be minimized. Therefore, it is included in the lag selection discussion and is selected by the lag length with the lowest value. Measuring the difference between given model and true model, the AIC has to be as low as possible, shown by Akaike (1973). A similar interpretation provides the SBIC and the HQIC. Luetkepohl (2005) discussed the theoretical advantage of SBIC and HQIC over the AIC and the FPE. In the data series of 6 indices, the likelihood-ratio (LR) tests selected a model with 4 lags. HQIC has chosen a model with two lags, whereas FPE, AIC and even the SBIC have selected a model with only one lag. Consequently, a one ARCH term and one GARCH term is used for the conditional variance equation of each indices. In following, table 5 shows the DCC estimation with GARCH(1) and ARCH(1).

Dynamic Conditional Correlation (DCC)							
log likelihood = 124365.0							
		Coef.	OPG Std.Err	z	P>|z|	[95% Conf.	Interval]
ARCH_FTSE	arch L1	0.0637757	0.003937	16.22	0.0000	0.0560691	.0714823
	garch L1	0.9284701	0.0013591	212.99	0.0000	0.9199264	.9370139
	_cons	1.32E-06	1.69E-07	7.79	0.0000	9.85E-07	1.65e-06
ARCH_DAX	arch L1	0.0656224	0.0035701	18.38	0.0000	0.0586252	.0726196
	garch L1	0.9247539	0.0039471	234.29	0.0000	0.9170178	.93249
	_cons	2.62E-06	2.58E-07	10.23	0.0000	2.12E-06	3.12e-06
ARCH_INDU	arch L1	0.048682	0.0027587	17.65	0.0000	0.0432751	.0540889
	garch L1	0.9431361	0.000756	289.66	0.0000	0.9367545	.9495178
	_cons	9.69E-07	1.09E-07	8.86	0.0000	7.55E-07	1.18e-06
ARCH_SP500	arch L1	0.0482413	0.0024765	19.48	0.0000	0.0433875	.0530952
	garch L1	0.944511	0.0028662	329.53	0.0000	0.9388934	.9501286
	_cons	9.41E-07	9.82E-08	9.58	0.0000	7.49E-07	1.13e-06
ARCH_SXXE	arch L1	0.0686716	0.0036709	18.71	0.0000	0.0614767	.0758664
	garch L1	0.9229969	0.0041044	224.88	0.0000	0.9149524	.931.0413
	_cons	2.32E-06	2.33E-07	9.98	0.0000	1.87E-06	2.78e-06
ARCH_IXIC	arch L1	0.0501756	0.0029842	16.81	0.0000	0.0443267	.0560245
	garch L1	0.9441076	0.0033041	285.74	0.0000	0.9376317	.9505834
	cons	1.24E-06	1.55E-07	7.99	0.0000	9.33E-07	1.54e-06
	corr(FTSE100, DAX)	0.8221963	0.0180374	45.57	0.0000	0.7866103	.8577157
	corr(FTSE100, INDU)	0.5322808	0.0386091	13.79	0.0000	0.4566083	.6079532
	corr(FTSE100, SP500)	0.5233292	0.0389469	13.44	0.0000	0.4469947	.5996637
	corr(FTSE100, SXXE)	0.8531915	0.0148766	57.35	0.0000	0.824034	.882349
	corr(FTSE100, IXIC)	0.478945	0.0412931	11.6	0.0000	0.398012	.5598779
	corr(DAX, INDU)	0.5584386	0.0367332	15.2	0.0000	0.4864428	.6304344
	corr(DAX, SP500)	0.550688	0.0370227	14.87	0.0000	0.4781249	.6232511
	corr(DAX, SXXE)	0.9538348	0.0056143	169.89	0.0000	0.9428309	.9648387
	corr(DAX, IXIC)	0.5290064	0.0384327	13.76	0.0000	0.4536796	.6043332
	corr(INDU, SP500)	0.9681275	0.0034649	279.41	0.0000	0.9613365	.9749185
	corr(INDU, SXXE)	0.5657075	0.0364892	15.5	0.0000	0.49419	.6372249
	corr(INDU, IXIC)	0.8703043	0.013504	64.45	0.0000	0.8438368	.8967717
	corr(SP500, SXXE)	0.5590736	0.0367229	15.22	0.0000	0.4870981	.6310491
	corr(SP500, IXIC)	0.9308737	0.0076038	122.42	0.0000	0.9159706	.9457769
	corr(SXXE, IXIC)	0.5248939	0.0387751	13.54	0.0000	0.4488861	.6008818
Adjustment	lambda1	0.0185426	0.0007269	25.51	0.0000	0.0171179	.0199674
	lambda2	0.9763659	0.0009138	1068.47	0.0000	0.9745749	.9781569

TABLE 5. DYNAMIC CONDITIONAL CORRELATION

As table 5 shows, all estimated conditional quasi-correlations are high and positive between the volatilities of the 6 different indices. For instance, the estimated conditional correlation between INDU and IXIC is 0.8703. This means that high volatility in the INDU is related to a high volatility in the IXIC and vice versa. The dynamic conditional correlations within the American indices are between 0.87 and 9.97. The European estimated correlations have in contrast to the American indices a little smaller interval, between 0.82 and 0.95. Finally, table 5 presents the results for the adjustment parameters λ_1 and λ_2. Both estimated values for λ_1 and λ_2 are statistically significant. The estimations for the CCC as well the VCC can be found in Appendix, table 6 and table 7.

The same methodologies of the DCC, CCC and VCC are used for the specific time frame of the DotCom, which is illustrated in the tables 8, 9 and 10. If $\lambda_1 = \lambda_2 = 0$, than the DCC model reduces the CCC model. Table 11 (and Table 12 for the DotCom time frame) shows the result of the Wald test - see Wald (1943) - with the null hypothesis that $\lambda_1 = \lambda_2 = 0$ at all conventional levels. The result below indicates that the assumption of constant (time invariant) conditional correlations supposed by the CCC model is too restrictive for the data set of 6 indices.

Wald-Test	H0: $\lambda_1 = \lambda_2 = 0$	
1)	[Adjustment]lambda1 - [Adjustment]lambda2 = 0	
2)	[Adjustment]lambda1 = 0	
	chi2(2)	5.5E+06
	Prob > chi2	0.0E+00

TABLE 11. WALD TEST

An interesting finding can be even seen in table 13, 14 and 15. Those tables indicate the different conditional correlation matrix and compared them with the null hypothesis that the correlation between different stock markets is lower during a bubble than sometimes else. The table on the right hand indicates that hypothesis. “Yes”

means, that the null hypothesis is right and is not rejected. Meaning that during the DotCom the correlation between the different indices were lower than in the time without bubble. “No” indicates that the conditional correlation is higher during the DotCom. Table 13 indicates the different conditional correlation in two different time frames. As one can see, every conditional correlation is higher in the full sample as in the DotCom time frame. The findings from the conditional correlation of the CCC and the VCC models confirm this result as well.

Dynamic Conditional Correlation (DCC): Full Sample

	FTSE100	DAX	NDU	SP500	SMF	IXC
FTSE100	1	0.8220	0.5222	0.5255	0.8532	0.1789
DAX	0.8220	1	0.5584	0.5507	0.9538	0.5290
INDU	0.5222	0.5584	1	0.9581	0.6627	0.8702
SP500	0.5344	0.5502	0.9667	1	0.5591	0.9409
SMF	0.8532	0.9538	0.6657	0.5591	1	0.5249
IXC	0.1789	0.5290	0.8702	0.9309	0.5219	1

Dynamic Conditional Correlation (DCC): Full Sample vs DotCom Bubble

	FTSE100	DAX	INDU	SP500	SMF	IXC
FTSE100	1	YES	YES	YES	YES	YES
DAX	YES	1	YES	YES	YES	YES
INDU	YES	YES	1	YES	YES	YES
SP500	YES	YES	YES	1	YES	YES
SMF	YES	YES	YES	YES	1	YES
IXC	YES	YES	YES	YES	YES	1

Dynamic Conditional Correlation (DCC): DotCom Bubble

	FTSE100	DAX	NDU	SP500	SMF	IXC
FTSE100	1	0.7034	0.4331	0.4595	0.7830	0.3608
DAX	0.7034	1	0.5361	0.5491	0.8527	0.4767
INDU	0.4221	0.5361	1	0.9121	0.4741	0.8710
SP500	0.4595	0.5491	0.913	1	0.5135	0.8615
SMF	0.7830	0.8527	0.4741	0.5135	1	0.4582
IXC	0.3608	0.4767	0.8710	0.8615	0.4583	1

TABLE 13. DYNAMIC CONDITIONAL CORRELATION- SAMPLE VS DOTCOM

Figure 9 visualizes the computed individually DCC plots for pair-wise countries with the different contagion source countries.

The break-point dates are represented by vertical dash circles, which indicate the two main crises, DotCom (1999-2001) as well the Subprime Crisis (2006-2007). An interesting outcome is that it seems - even with a general high correlation among the contingents - that during a bubble or crisis the contagion decreases. Having a closer look to the DotCom bubble time, another graphs are plotted, can be seen in figure 9. The time frame is July 1998 to October 2001.

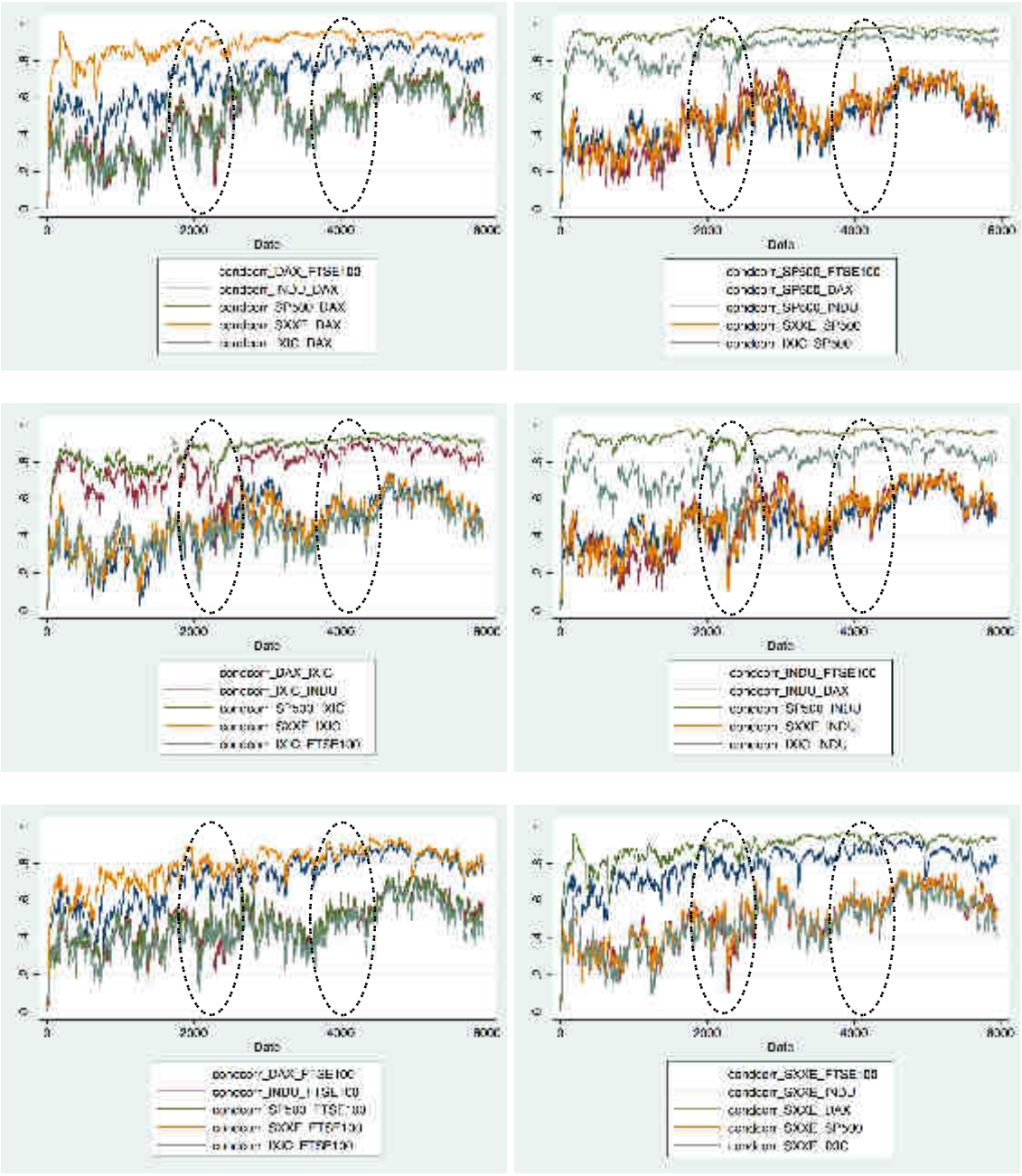

FIGURE 9. ESTIMATED DYNAMIC CORRELATION COEFFICIENTS

Having estimated the DCC model, the conditional variance is forecasted for the next 50 time periods into the future. Figure 10 shows the result of those forecasts. From those conditional variances one can see the impact of crisis to the different stock markets. As figure 11 illustrates that the variance in period of the DotCom bubble persist longer than the subprime crisis. On the other hand, it is shown that during the subprime

crisis there was an even higher variance. Getting as well a deeper look to the DotCom bubble, figure 12 illustrates this specific time frame.

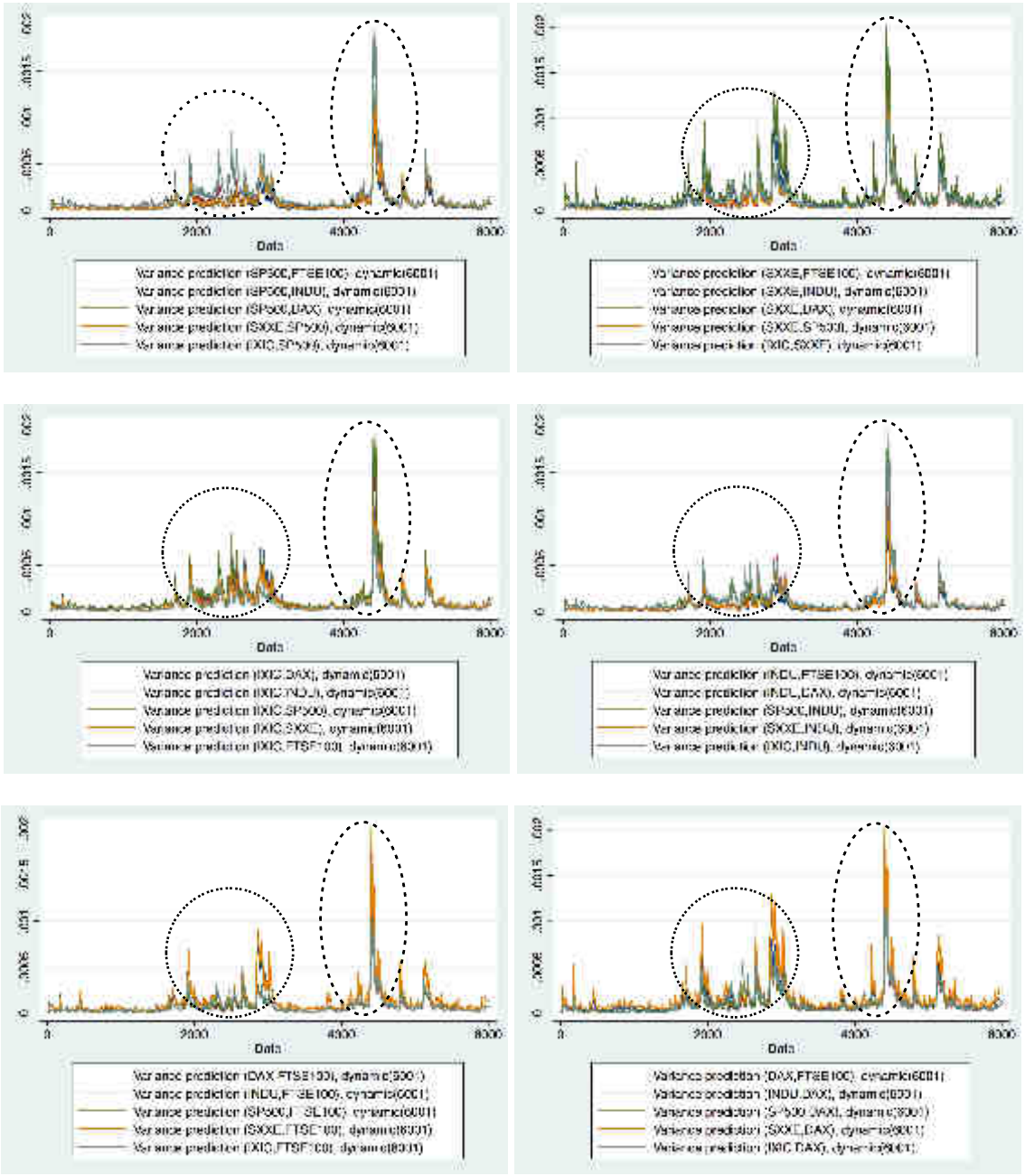

FIGURE 10. CONDITIONAL VARIANCES OF THE RETURNS

6 SUMMARY & CONCLUSION

Given the main objective of this paper to analyze the phenomenon of financial contagion between stock market returns of different continents, the empirical analysis in this paper examined the co-movements and spillover effects in the stock market returns of American and European markets between 1990 and 2014. Three multivariate conditional correlation volatility models were used: the DCC-GARCH by Engle and Sheppard (2001), the CCC by Bollerslev (1990) and the VCC by Tse and Tsui (2002). Throughout the work these methodologies were applied to daily returns of SP500, INDU and IXIC (all United States), FTSE100 (UK), DAX (Germany) and SXXE (Europe) for the period from 12/01/1990 to 01/01/2015 and confronted with other models most widespread in the literature on the subject. The result does not reject the hypothesis of higher contagion in American and European stock markets during crisis. Especially, during the DotCom bubble there was contagion, but not that significant as observed for the full time sample. All three contagion tests show that multivariate estimates were significant for all returns in those models and therefore, demonstrate that there have been changes in the structure of dependence between American and European markets. This can be caused by different facts, like micro- and macroeconomic factors or even investors' behavior. Without any doubt, those impacts can distort the efficient allocation of investment portfolios and should take into consideration regarding the diversification analysis. Especially regarding the DotCom bubble, amplifying losses arising from the negative shocks triggered by the extreme optimism about the new technology industry, the Internet. Those typical human behavior occurs because the structure of those financial crises depends on either misjudgments or negligence in fundamental values, wheth-

er on a macroeconomic or company scale, by agents - rational and irrational - with the power to influence the behavior of an entire market, as discussed in Sector 3.4.

The statistical significance of DCC-estimations indicates that the conditional correlations were dynamic. In fact, the variance-covariance analysis produced useful information on the dynamic correlations between the three developed markets, and for each pairwise series, the dynamic conditional correlations vary considerably from their respective constant correlations, implying the absence of any constant correlation between the stock markets under study.

The empirical findings showed that the American and European (as well separately U.K. and German) markets were highly correlated since the end of 1995 with the beginning of the DotCom bubble. These results confirm the presence of spillover effects between those stock markets.

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8 APPENDIX

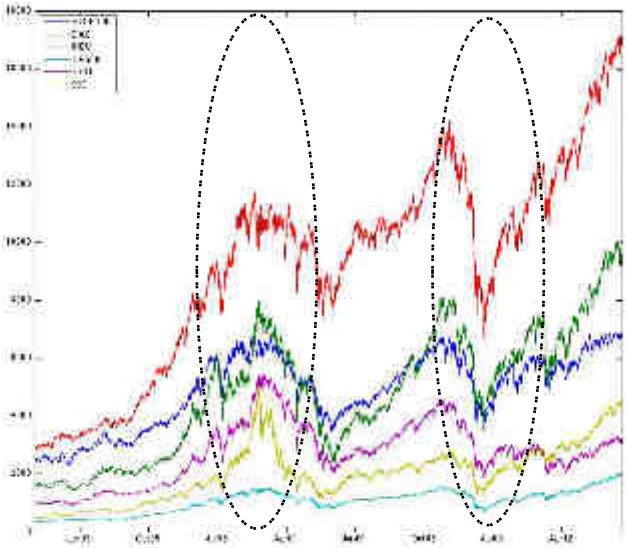

FIGURE 5. ALL STOCK MARKET INDICES

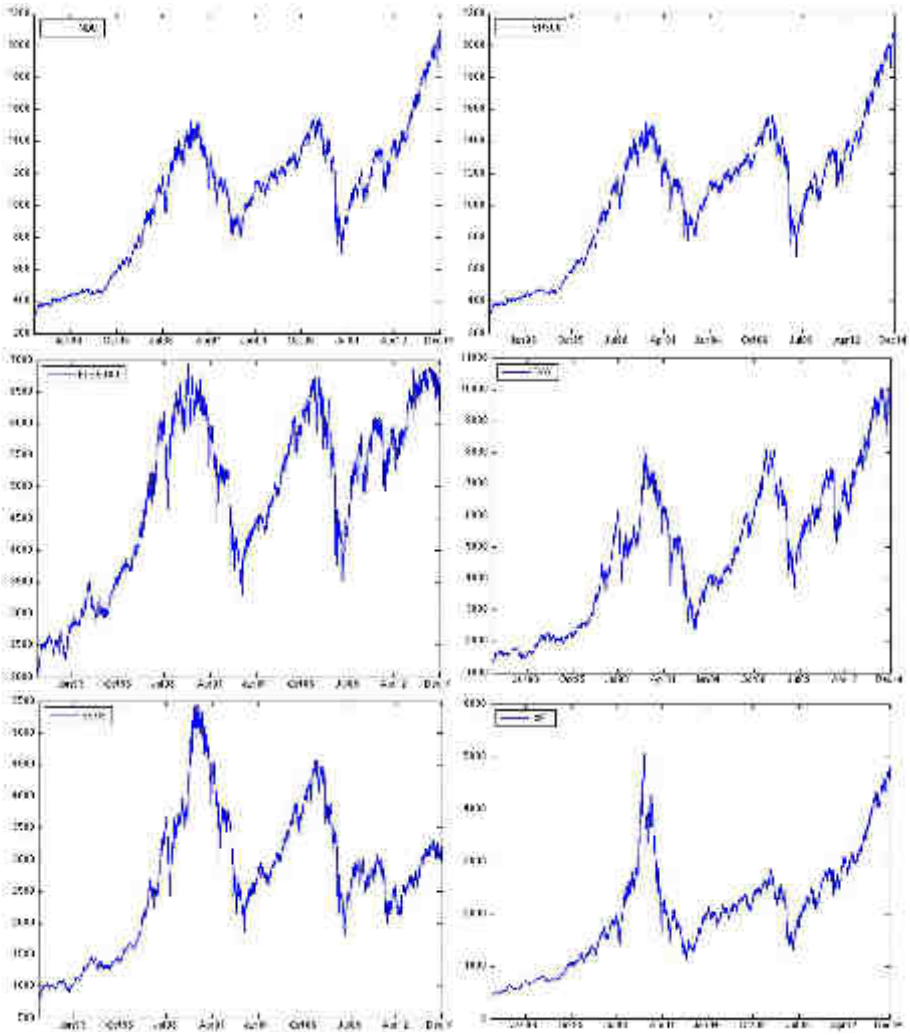

FIGURE 6. STOCK MARKET INDICES

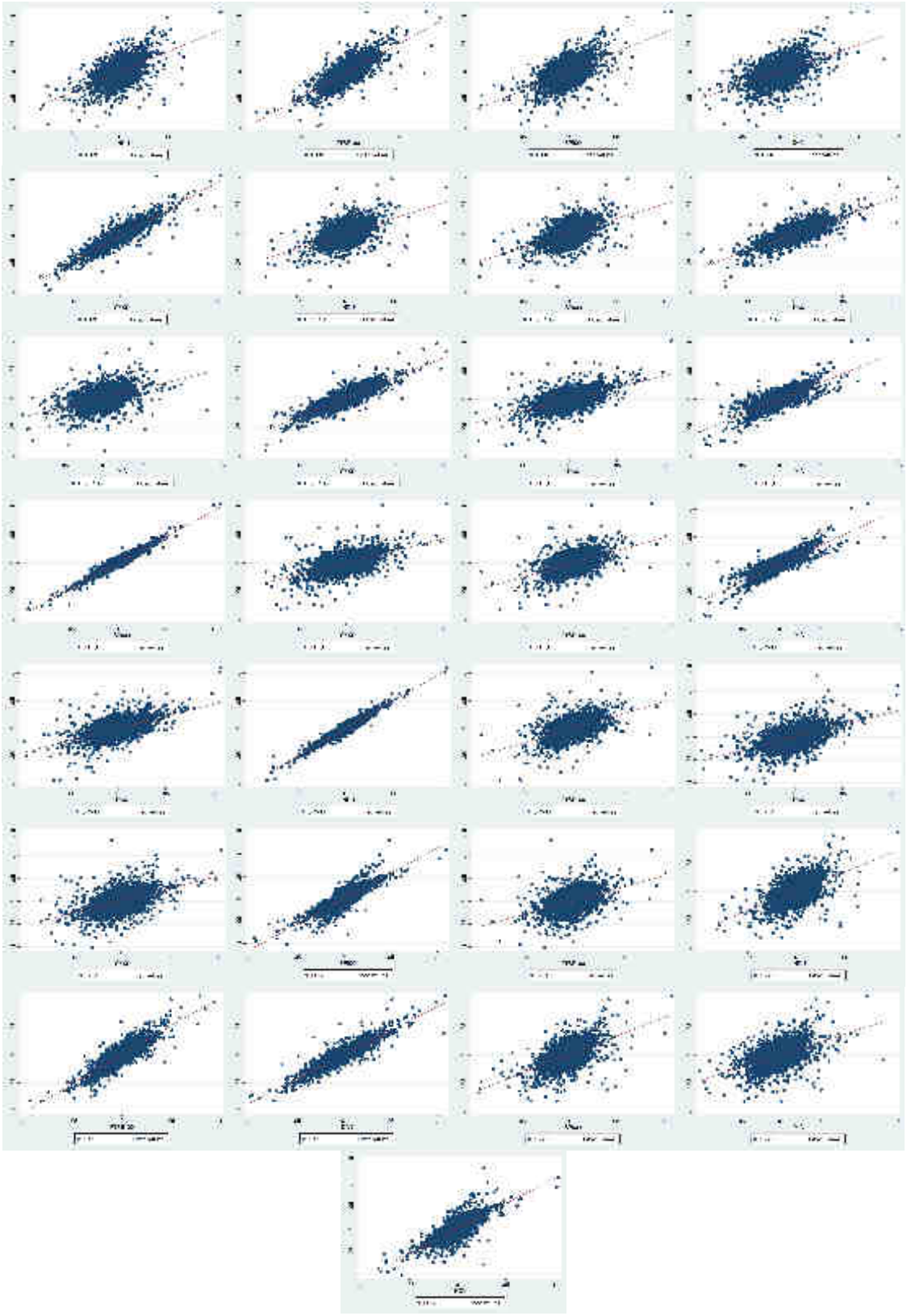

FIGURE 8. SCATTER PLOT EVERY INDICES WITH EACH OTHER

Constant Conditional Correlation (CCC)
log Likelihood = 132453.3

		Coef.	OPG Std.Err	z	P>|z|	[95% Conf.	Interval]
ARCH_FTSE	arch L1	0.0566935	0.0043693	12.98	0.0000	0.0481296	.065257
	garch L1	0.9170612	0.0063143	145.24	0.0000	0.9046854	.9294369
	_cons	2.26E-06	2.72E-07	8.69	0.0000	1.83E-06	2.80e-06
ARCH_DAX	arch L1	0.0567807	0.0038654	14.69	0.0000	0.0492047	.0643568
	garch L1	0.912734	0.0055912	163.24	0.0000	0.9017754	.9236926
	_cons	4.71E-06	4.16E-07	11.31	0.0000	3.89E-06	5.52e-06
ARCH_INDU	arch L1	0.0488243	0.003367	14.5	0.0000	0.0422251	.0554235
	garch L1	0.9220098	0.0052205	176.8	0.0000	0.9127778	.9332419
	_cons	2.33E-06	2.20E-07	10.59	0.0000	1.90E-06	2.76e-06
ARCH_SP500	arch L1	0.0487081	0.0029914	16.28	0.0000	0.0428451	.0545712
	garch L1	0.9252955	0.0044994	205.65	0.0000	0.9164769	.934.142
	_cons	2.25E-06	1.93E-07	11.66	0.0000	1.87E-06	2.62e-06
ARCH_SXXE	arch L1	0.0572276	0.003592	15.93	0.0000	0.0501874	.0642677
	garch L1	0.9122415	0.0053578	170.26	0.0000	0.9017403	.9227427
	_cons	4.08E-06	3.57E-07	11.44	0.0000	3.39E-06	4.79e-06
ARCH_IXIC	arch L1	0.0564031	0.0041244	13.68	0.0000	0.0483193	.0644868
	garch L1	0.9201043	0.0056225	163.62	0.0000	0.9090824	.9311262
	_cons	3.29E-06	3.24E-07	10.15	0.0000	2.66E-06	3.93e-06
	corr(FTSE100, DAX)	0.7207753	0.0062651	115.05	0.0000	0.708496	.7330547
	corr(FTSE100, INDU)	0.4826002	0.0098302	49.7	0.0000	0.1671374	.5030629
	corr(FTSE100, SP500)	0.4890056	0.0098663	49.56	0.0000	0.1696681	.5083431
	corr(FTSE100, SXXE)	0.7949716	0.0048163	165.06	0.0000	0.7855339	.8044113
	corr(FTSE100, IXIC)	0.4502268	0.0103578	43.55	0.0000	0.1299651	.4701885
	corr(DAX, INDU)	0.500551	0.009725	51.47	0.0000	0.1814903	.5196117
	corr(DAX, SP500)	0.5018937	0.0097125	51.69	0.0000	0.1829576	.5210298
	corr(DAX, SXXE)	0.9017632	0.0024279	371.42	0.0000	0.8970016	.9065248
	corr(DAX, IXIC)	0.4781202	0.0100103	47.76	0.0000	0.1585003	.4977401
	corr(INDU, SP500)	0.9507579	0.0012527	758.94	0.0000	0.9483026	.9532132
	corr(INDU, SXXE)	0.5975809	0.009623	52.75	0.0000	0.1887201	.5264416
	corr(INDU, IXIC)	0.7935335	0.0048023	165.24	0.0000	0.7841211	.8029458
	corr(SP500, SXXE)	0.5123537	0.0095535	53.73	0.0000	0.1946292	.5320783
	corr(SP500, IXIC)	0.8822718	0.0028555	309.32	0.0000	0.877675	.8868685
	corr(SXXE, IXIC)	0.4854565	0.0099103	48.99	0.0000	0.4660527	.5048604

TABLE 6. CONSTANT CONDITIONAL CORRELATION

Varying conditional correlation (VCC)
log Likelihood = 134214.6

		Coef.	OPG Std.Err	z	P>|z|	[95% Conf.	Interval]
ARCH_FTSE	arch L1	0.0544271	0.0035572	15.39	0.0000	0.0474943	.0613599
	garch L1	0.9550071	0.004138	225.96	0.0000	0.9268968	.9431174
	_cons	1.10E-06	1.46E-07	7.49	0.0000	8.09E-07	1.38e-06
ARCH_DAX	arch L1	0.0576292	0.003266	17.65	0.0000	0.0512281	.0640304
	garch L1	0.9293052	0.003799	244.62	0.0000	0.9218593	.9367512
	_cons	2..4E-06	2.18E-07	9.84	0.0000	1.72E-06	2.57e-06
ARCH_INDU	arch L1	0.0421653	0.0025385	16.29	0.0000	0.0370924	.0472392
	garch L1	0.9482432	0.0031278	303.17	0.0000	0.9421119	.9543726
	_cons	8..4E-07	9.35E-08	8.7	0.0000	6.31E-07	9.97e-07
ARCH_SP500	arch L1	0.0423039	0.0023652	17.89	0.0000	0.0376682	.0469397
	garch L1	0.948913	0.0027878	340.29	0.0000	0.9434491	.9543769
	_cons	8.00E-07	8.36E-08	9.56	0.0000	6.36E-07	9.64e-07
ARCH_SXXE	arch L1	0.059196	0.0032924	17.97	0.0000	0.052741	065651
	garch L1	0.9291395	0.0038423	241.75	0.0000	0.9216067	.9366722
	_cons	1.84E-06	1.93E-07	9.55	0.0000	1.46E-06	2.22e-06
ARCH_IXIC	arch L1	0.045179	0.0029277	15.43	0.0000	0.0394407	.0509172
	garch L1	0.9472075	0.0033581	282.78	0.0000	0.940725	.9538101
	_cons	1.1..E-06	1.41E-07	7.82	0.0000	8.29E-07	1.38e-06
	corr(FTSE100, DAX)	0.8283366	0.0111773	58.43	0.0000	0.8005496	.8561237
	corr(FTSE100, INDU)	0.5972023	0.0278819	21.42	0.0000	0.5425548	.6518497
	corr(FTSE100, SP500)	0.5944934	0.0279776	21.27	0.0000	0.5397161	.6492687
	corr(FTSE100, SXXE)	0.8797772	0.0112918	77.91	0.0000	0.8576458	.9019087
	corr(FTSE100, IXIC)	0.5510388	0.0298534	18.47	0.0000	0.1925864	.6095113
	corr(DAX, INDU)	0.6215571	0.0265202	23.55	0.0000	0.5725785	.6705357
	corr(DAX, SP500)	0.6244122	0.0265098	23.55	0.0000	0.572451	.6763701
	corr(DAX, SXXE)	0.9515905	0.0045002	211.76	0.0000	0.9427704	.9604107
	corr(DAX, IXIC)	0.6110261	0.0277104	22.05	0.0000	0.5567148	.6653371
	corr(INDU, SP500)	0.9798125	0.0024536	399.34	0.0000	0.9750035	.9846211
	corr(INDU, SXXE)	0.6262268	0.0261806	23.92	0.0000	0.5749138	.6775398
	corr(INDU, IXIC)	0.8951593	0.0100909	88.71	0.0000	0.8753814	.9149372
	corr(SP500, SXXE)	0.6291261	0.026123	24.08	0.0000	0.5779263	.6803265
	corr(SP500, IXIC)	0.9442859	0.0057635	163.84	0.0000	0.9329896	.9555823
	corr(SXXE, IXIC)	0.6000661	0.0277685	21.61	0.0000	0.5456112	.6544916
Adjustment	lambda1	0.0098982	0.0006687	14.8	0.0000	0.0083875	.0114088
	lambda2	0.9857504	0.0031007	978.88	0.0000	0.9837767	.9877241

TABLE 7. VARYING CONDITIONAL CORRELATION

Dynamic Conditional Correlation (DCC)							
log likelihood =	-16154.15						
		Coef.	OPG Std.Err.	z	P>|z|	[95% Conf. Interval]	
ARCH_FTS	arch L1	0.04813	0.01168	4.12000	0.00000	0.0252721	0.071027
	garch L1	0.92158	0.02165	42.58000	0.00000	0.8791574	0.9640071
	_cons	0.00001	0.00000	2.31000	0.02100	7.58E-07	9.33E-06
ARCH_DAX	arch L1	0.05385	0.00977	5.51000	0.00000	0.0347031	0.0729956
	garch L1	0.92078	0.01626	56.64000	0.00000	0.8889207	0.9526409
	_cons	0.00001	0.00000	2.92000	0.00400	2.25E-06	0.0000115
ARCH_IND	arch L1	0.05979	0.01196	5.01000	0.00000	0.0363957	0.0831853
	garch L1	0.85660	0.02982	29.52000	0.00000	0.79973	0.9134672
	_cons	0.00001	0.00000	3.71000	0.00000	6.18E-06	0.000002
ARCH_SP5	arch L1	0.06888	0.01054	6.35000	0.00000	0.0482315	0.0895359
	garch L1	0.86026	0.02075	41.45000	0.00000	0.8195855	0.9009432
	_cons	0.00001	0.00000	4.66000	0.00000	7.39E-06	0.0000181
ARCH_SXX	arch L1	0.0497893	0.0078007	6.31	0	0.0339015	0.0644772
	garch L1	0.933348	0.0124432	75.01	0	0.9089598	0.9577361
	_cons	4.46E-06	1.65E-06	2.7	0.007	1.23E-06	7.70E-06
ARCH_IXIC	arch L1	0.0910506	0.0159422	5.71	0	0.0598043	0.1222968
	garch L1	0.8756518	0.0207303	42.24	0	0.8350212	0.9162824
	_cons	0.0000196	5.22E-06	3.72	0	9.21E-06	0.0000297
	corr(FTSE100, DAX)	0.7033607	0.0286747	24.53	0	0.6471604	0.759561
	corr(FTSE100, INDU)	0.4220634	0.0466705	9.04	0	0.3305233	0.5136036
	corr(FTSE100, SP500)	0.4594516	0.0447188	10.27	0	0.3718043	0.5470989
	corr(FTSE100, SXXP)	0.7819671	0.0220857	35.4	0	0.7387191	0.8252151
	corr(FTSE100, IXIC)	0.3807854	0.0481512	7.91	0	0.2864108	0.4751599
	corr(DAX, INDU)	0.5303848	0.0415188	12.68	0	0.4484214	0.6123483
	corr(DAX, SP500)	0.5460873	0.0405044	13.56	0	0.4667002	0.6284744
	corr(DAX, SXXP)	0.8927438	0.0113809	78.37	0	0.8704181	0.9150696
	corr(DAX, IXIC)	0.4767012	0.0437766	10.89	0	0.3909007	0.5625017
	corr(INDU, SP500)	0.9120803	0.0096324	94.69	0	0.8932012	0.9309594
	corr(INDU, SXXP)	0.674138	0.0441582	10.74	0	0.3875875	0.5606885
	corr(INDU, IXIC)	0.6709701	0.03128	21.45	0	0.6096625	0.7322777
	corr(SP500, SXXP)	0.5134809	0.0417795	12.29	0	0.4315947	0.5953672
	corr(SP500, IXIC)	0.8615081	0.014567	59.14	0	0.8329573	0.8900588
	corr(SXXP, IXIC)	0.4582415	0.0444068	10.32	0	0.3712058	0.5452772

TABLE 8. DYNAMIC CONDITIONAL CORRELATION DOTCOM

Constant Conditional Correlation (CCC)							
log likelihood =	16307.2						
		Coef.	OPG Std.Err.	z	P>|z|	[95% Conf. Interval]	
ARCH_FTS	arch L1	0.0405604	0.0114597	3.55	0	0.0181399	0.063121
	garch L1	0.9266378	0.0242197	38.26	0	0.879168	0.9741076
	_cons	5.35E-06	2.54E-06	2.11	0.035	3.83E-07	0.0000103
ARCH_DAX	arch L1	0.0436848	0.0094803	4.61	0	0.0251038	0.0622659
	garch L1	0.9304494	0.0172803	53.84	0	0.8965805	0.9643182
	_cons	7.12E-06	2.64E-06	2.69	0.007	1.92E-06	0.0000123
ARCH_IND	arch L1	0.0505734	0.0118154	4.28	0	0.0274155	0.0737312
	garch L1	0.8473798	0.0385115	22.01	0	0.7758183	0.9189413
	_cons	0.0000168	4.85E-06	3.43	0.001	7.15E-06	0.0000261
ARCH_SP5	arch L1	0.0591682	0.0109587	5.39	0	0.0376899	0.0806466
	garch L1	0.8526132	0.0251974	33.84	0	0.8032271	0.9019992
	_cons	0.0000165	3.63E-06	4.54	0	9.38E-06	0.0000236
ARCH_SXX	arch L1	0.0386898	0.0068942	5.61	0	0.0251775	0.0522022
	garch L1	0.9405348	0.0128117	73.41	0	0.9154245	0.9656453
	_cons	5.07E-06	1.85E-06	2.74	0.006	1.45E-06	8.69E-06
ARCH_IXIC	arch L1	0.0850577	0.0169785	5.01	0	0.0517803	0.118335
	garch L1	0.8745564	0.0237552	36.82	0	0.8279971	0.9211157
	_cons	0.000025	6.65E-06	3.75	0	0.0000119	0.000038
	corr(FTSE100, DAX)	0.7195707	0.0169403	42.48	0	0.6863583	0.7527831
	corr(FTSE100, INDU)	0.4141423	0.0290111	14.28	0	0.3572815	0.4710029
	corr(FTSE100, SP500)	0.4467607	0.0280144	15.95	0	0.3918534	0.5016679
	corr(FTSE100, SXXP)	0.7963725	0.0129173	61.65	0	0.771055	0.82169
	corr(FTSE100, IXIC)	0.3990754	0.0294381	13.56	0	0.3413778	0.4567729
	corr(DAX, INDU)	0.475894	0.0272097	17.49	0	0.422564	0.5292239
	corr(DAX, SP500)	0.5030593	0.0262335	19.18	0	0.4516427	0.554476
	corr(DAX, SXXP)	0.8928582	0.0070794	126.12	0	0.8789827	0.9067336
	corr(DAX, IXIC)	0.4721105	0.027278	17.31	0	0.4186466	0.5255744
	corr(INDU, SP500)	0.9113788	0.0059519	153.07	0	0.8996938	0.9230639
	corr(INDU, SXXP)	0.4391554	0.028335	15.5	0	0.3836179	0.4946929
	corr(INDU, IXIC)	0.6583122	0.0198525	33.16	0	0.6194018	0.6972225
	corr(SP500, SXXP)	0.477985	0.0270862	17.65	0	0.424897	0.531073
	corr(SP500, IXIC)	0.8567238	0.0093123	92	0	0.838472	0.8749756
	corr(SXXP, IXIC)	0.4572583	0.0277582	16.47	0	0.4028336	0.5116831

TABLE 9. CONSTANT CONDITIONAL CORRELATION DOTCOM

Varying conditional correlation (VCC)							
log likelihood = 16415.15							
			OPG				
		Coef.	Std.Err	z	P>|z|	[95% Conf. Interval]	
ARCH_FTS	arch L1	0.0446714	0.0115974	3.85	0	0.0218428	0.067402
	garch L1	0.9233681	0.0228421	40.42	0	0.8785985	0.9681378
	_cons	5.16E-06	2.32E-06	2.23	0.026	6.20E-07	9.70E-06
ARCH_DAX	arch L1	0.0518547	0.0107783	4.81	0	0.0307286	0.0729808
	garch L1	0.9209443	0.0184283	49.97	0	0.8848236	0.957065
	_cons	7.40E-06	2.67E-06	2.77	0.006	2.17E-06	0.0000126
ARCH_IND	arch L1	0.0669599	0.0140671	4.76	0	0.0393989	0.094521
	garch L1	0.8381195	0.0340613	24.61	0	0.7713627	0.9048763
	_cons	0.000016	4.34E-06	3.69	0	7.53E-06	0.0000245
ARCH_SP5	arch L1	0.0770498	0.0126339	6.1	0	0.0522878	0.1018118
	garch L1	0.844753	0.0229161	36.86	0	0.7998382	0.8896677
	_cons	0.0000153	3.18E-06	4.81	0	9.07E-06	0.0000216
ARCH_SXX	arch L1	0.0445475	0.0078917	5.64	0	0.0290802	0.060015
	garch L1	0.9342018	0.013852	67.44	0	0.9070524	0.9613511
	_cons	5.17E-06	1.89E-06	2.73	0.006	1.46E-06	8.88E-06
ARCH_IXI	arch L1	0.1013787	0.0186211	5.44	0	0.064882	0.1378754
	garch L1	0.8602525	0.0235111	36.58	0	0.8141815	0.9063234
	_cons	0.000025	5.43E-06	3.89	0	0.0000124	0.0000376
	corrFTSE100, DAX)	0.7166285	0.0192357	37.26	0	0.6788274	0.7543298
	corrFTSE100, INDU)	0.4289278	0.0323449	13.26	0	0.365533	0.4923226
	corrFTSE100, SP500)	0.4582491	0.0313423	14.62	0	0.3968184	0.5196798
	corrFTSE100, SXXE)	0.7963533	0.0146158	54.48	0	0.7677068	0.8249998
	corrFTSE100, IXIC)	0.4052418	0.0330253	12.27	0	0.3405055	0.4699781
	corrDAX, INDU)	0.4961525	0.0303153	16.37	0	0.4367357	0.5555694
	corrDAX, SP500)	0.5201836	0.029428	17.68	0	0.4624858	0.5778815
	corrDAX, SXXE)	0.8933443	0.0079941	111.75	0	0.8776762	0.9090136
	corrDAX, IXIC)	0.4828363	0.0306359	15.76	0	0.4227912	0.5428815
	corrINDU, SP500)	0.9203374	0.0063063	145.95	0	0.9080374	0.9327575
	corrINDU, SXXE)	0.4556004	0.031535	14.45	0	0.3976753	0.5215255
	corrINDU, IXIC)	0.6839871	0.021553	31.74	0	0.6417441	0.7262301
	corrSP500, SXXE)	0.438375	0.0302559	14.49	0	0.3790668	0.4976832
	corrSP500, IXIC)	0.8632502	0.0102155	84.49	0	0.8432304	0.8832699
	corrSXXE, IXIC)	0.4720598	0.031019	15.23	0	0.4121049	0.5338146
Adjustment	lambda1	0.1174383	0.0325576	3.61	0	0.0536265	0.1812501
	lambda2	0.0757581	0.2598084	0.29	0.771	-0.433447	0.5849632

TABLE 10. VARYING CONDITIONAL CORRELATION DOTCOM

Constant Conditional Correlation (CCC): Full Sample

	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.7208	0.4846	0.4890	0.7950	0.4502
DAX	0.7208	1	0.5006	0.5020	0.9018	0.4781
INDU	0.4835	0.5006	1	0.9505	0.5076	0.7935
SP500	0.4890	0.5020	0.9505	1	0.5134	0.8033
SXXE	0.7950	0.9018	0.5076	0.5131	1	0.4833
IXIC	0.4502	0.4781	0.7935	0.8033	0.4833	1

Constant Conditional Correlation (CCC): Full Sample vs DotCom Bubble

	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	YES	YES	YES	NO	YES
DAX	YES	1	YES	NO	YES	YES
INDU	YES	YES	1	YES	YES	YES
SP500	YES	NO	YES	1	YES	YES
SXXE	NO	YES	YES	YES	1	YES
IXIC	YES	YES	YES	YES	YES	1

Constant Conditional Correlation (CCC): DotCom Bubble

	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.7196	0.4141	0.4468	0.7964	0.3991
DAX	0.7196	1	0.4759	0.5031	0.8929	0.4721
INDU	0.4141	0.4759	1	0.9114	0.4392	0.6583
SP500	0.4468	0.5031	0.9114	1	0.4780	0.8567
SXXE	0.7964	0.8929	0.4392	0.4780	1	0.4573
IXIC	0.3991	0.4721	0.6583	0.8567	0.4573	1

TABLE 14. CONSTANT CONDITIONAL CORRELATION- SAMPLE VS DOTCOM

Varying conditional correlation (VCC): Full Sample

	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.8283	0.5972	0.5946	0.8798	0.6610
DAX	0.8283	1	0.6246	0.6244	0.9516	0.6110
INDU	0.5972	0.6246	1	0.9798	0.6262	0.8952
SP500	0.5945	0.6244	0.9798	1	0.6291	0.8944
SXXE	0.8798	0.9516	0.6262	0.6291	1	0.6001
IXIC	0.6610	0.6110	0.8952	0.8944	0.6001	1

Varying conditional correlation (VCC): Full Sample vs DotCom Bubble

	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	YES	YES	YES	YES	YES
DAX	YES	1	YES	YES	YES	YES
INDU	YES	YES	1	YES	YES	YES
SP500	YES	YES	YES	1	YES	YES
SXXE	YES	YES	YES	YES	1	YES
IXIC	YES	YES	YES	YES	YES	1

Varying conditional correlation (VCC): DotCom Bubble

	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.7166	0.4289	0.4582	0.7964	0.4052
DAX	0.7166	1	0.4962	0.5202	0.8933	0.4828
INDU	0.4289	0.4962	1	0.9204	0.4595	0.8640
SP500	0.4582	0.5202	0.9204	1	0.4884	0.8033
SXXE	0.7964	0.8933	0.4595	0.4884	1	0.4730
IXIC	0.4052	0.4828	0.8640	0.8033	0.4730	1

TABLE 15. VARYING CONDITIONAL CORRELATION- SAMPLE VS DOTCOM

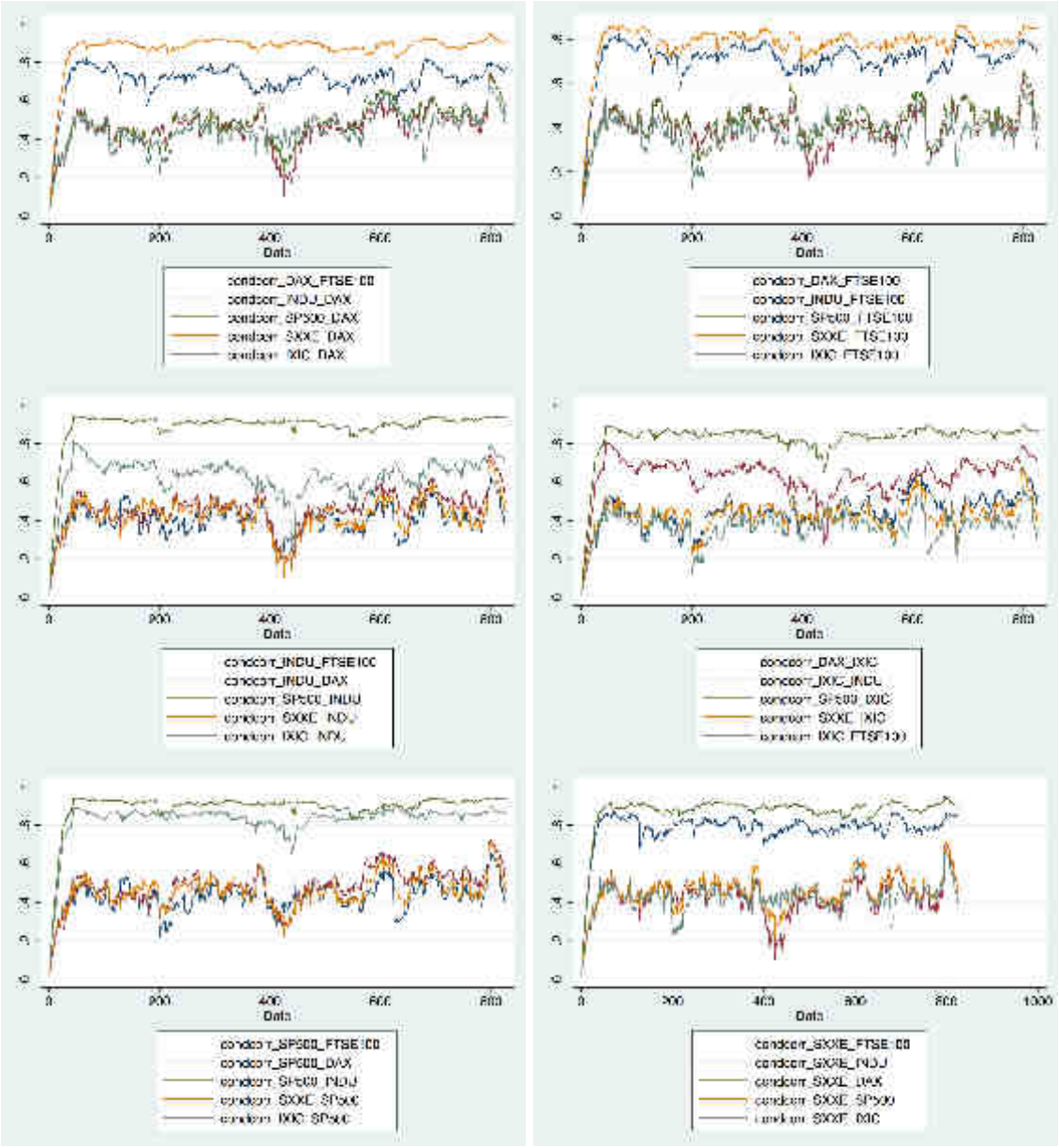

FIGURE 11. ESTIMATED DYNAMIC CORRELATION COEFFICIENTS DOTCOM

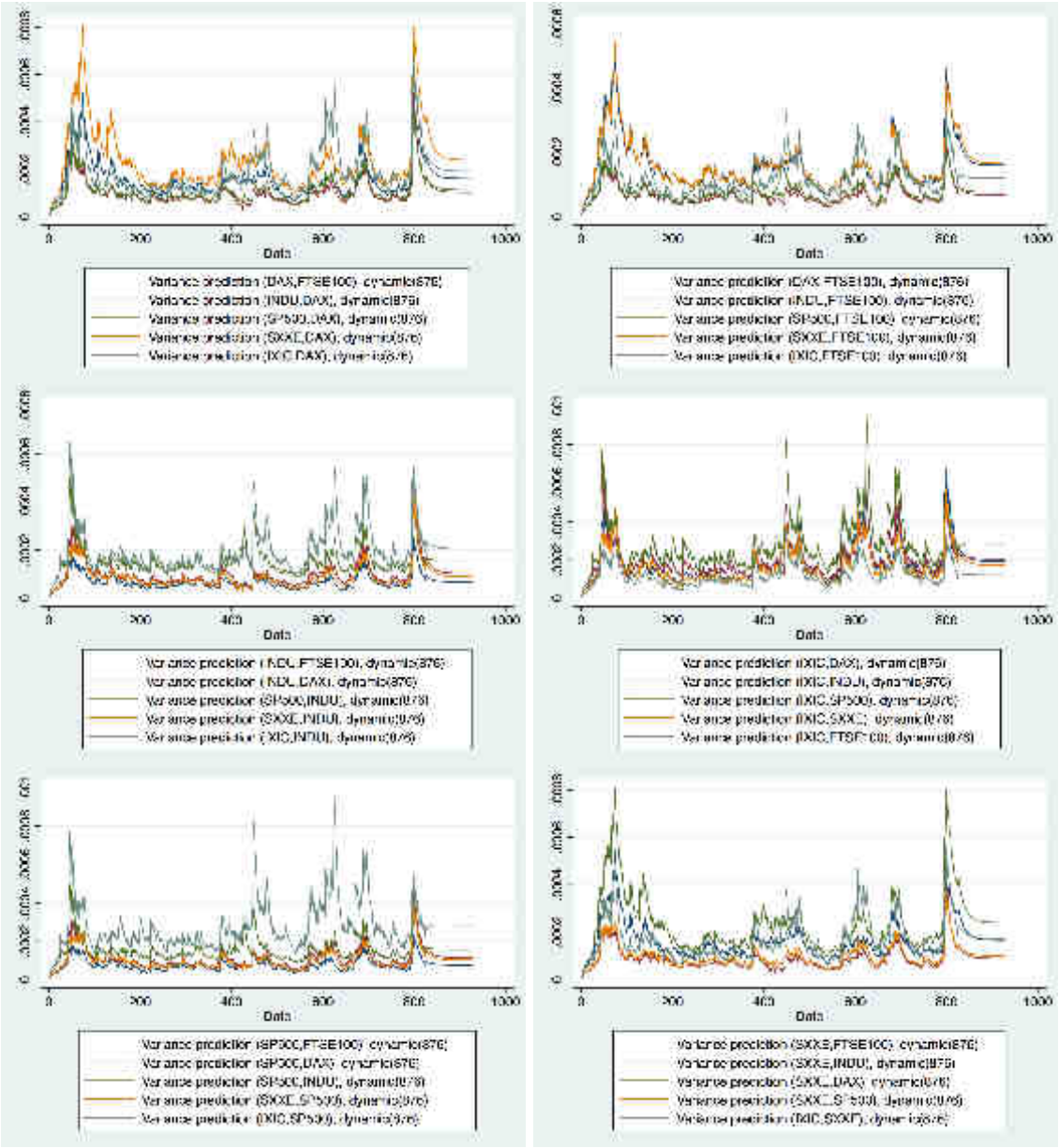

FIGURE 12. CONDITIONAL VARIANCES OF THE RETURNS DOTCOM

Wald-Test	II0:	
1)	[Adjustment]lambda1 - [Adjustment]lambda2 = 0	
2)	[Adjustment]lambda1 = 0	
	chi2(2)	17776.87
	Prob > chi2	0.0000

TABLE 12. WALD-TEST DOTCOM TIME FRAME