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ECONOMETRICS | RESEARCH ARTICLE

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

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economics & finance

Maximilian-Benedikt Herwarth Kohn¹ and Pedro L. Valls Pereira^{2*}

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 as on one hand as an econometrics explanation 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 prove the presence of structural changes during financial crisis.

Subjects: Statistics for Business, Finance & Economics; Econometrics; International Economics

Keywords: speculative bubbles; behavioral finance; financial contagion DCC

AMS subject classifications: G01; G02; C58; C19

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, Neal, & Wandschneider, 2006; Ofek & Richardson, 2001).

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

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PUBLIC INTEREST STATEMENT

The deviation of market prices from fundamental values is a phenomenon present during pricingbubbles. The DotCom bubble is one of them and this research focus on volatility models and try to answer the international markets, phenomena of high correlated market. In those highly integrated markets any shock in a single market can lead to a spillover to other markets characterizing contagious between market. In this research, we found contagious during the DotCom bubbles and also during the Sub-prime crisis of 2008. These results can have some implications in global economies in terms of output growth, unemployment, etc.





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focused on volatility models and tried to answer the international markets' phenomena of high correlated markets.

In fact, 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 spillover 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 spillover 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 spillover 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, Ungureanu, Vilag, and Stoia (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, Dandapani, and Bhattacharya (1994)—on correlation analyses tried to develop new measures and techniques by including comovements, 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) Is it observed a contagion effect between the American and European stock markets in the presence of price bubbles, like the DotCom bubble?
- (2) 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 correlation (VCC) by Tse and Tsui (002). Nevertheless, the main focus lies on the DCC-GARCH model.

The paper is organized as follows: Section 2 gives a short overview about the literatures of price bubbles and financial contagion. Section 3 defines generally price-bubbles and their development, subsequently the DotCom bubble is explained as well shortly analyzed. Section 4 starts with a short descriptive statistic of the considered data-set, describes the empirical strategy according to test for financial contagion and presents the results according to previous strategies. The Section 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 (1990) 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 instance, Kindleberger and Aliber (2005) 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 (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 (2005) 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 (2005) and Keynes (1935). This paper analyzes the technology-bubble—often mentioned as the DotCom-bubble. Ofek and Richardson (2001) were one of the first authors, who explained the internet bubble in the 1990s. 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. (1990) gives a good overview over the past famous bubbles and concludes that a bubble is a present phenomenon and will occur frequently.

From the econometrics point of view, several attempts to develop econometric tests have been made in the literature going back some decades (see Gurkaynar, 2008, for a recent review). But the papers by Phillips, Shi, and Yu (2013) and Phillips, Wu, and YU (2011) recently proposed a recursive method which can detect exuberance in asset price series during an inflationary phase. The method is especially effective when there is a single bubble episode in the sample data, as in the 1990s Nasdaq episode analyzed in the Phillips, Wu, and YU (2011) and this methodology is used in this paper to determined the time period of the Dot-Com Bubble.¹.

2.2. Financial contagion

The literature about contagion effect in financial markets is that extensive to re-view here fully. The surveys from Kindleberger (1978), Kaminsky, Reinhart, and Vegh (2003) and Bae, Karolyi, and Stulz (2003) are only some of those, which have to be mentioned. In general, the focus of most literature 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 an-other 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, de P Filleti, Hotta, and Zevallos (2008) analyzed the contagion between the Latin American economies and two emerging markets. Armada, Leitão, and Lobão (2011) tested the contagion effect between the financial markets of nine developed countries and Azad (2009) for the Asian market. Horta, Medes, and Vierra (2008) and as well Arruda and Pereira (2013) analyzed the contagion effects during the US Subprime crisis. Marçal, Pereira, Martins, and Nakamura (2011) evaluated the contagion in the financial crisis of Asia and Latin America. Rotta and Pereira (2016) evaluates the financial contagion between stock market returns of the United States (S&P500), United Kingdom (FTSE100), Brazil (IBOVESPA), and South Korea (KOSPI) from 1st of February 2003 to 20 of September 2012 using Regime Switching Dynamic Correlation (RSDC), originally presented by Pelletier (2006). A modification was made in the original RSDC model, the introduction of the GJR-GARCH-N and also GJR-GARCH-t

Regarding to the technology-bubble, Anderson, Brooks, and Katsaris (2010) studied the proliferation of the technology-bubble. Most of the studies applied variations of (Engle & Sheppard, 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.

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.

Table 1. Overview of empiri	cal researches	
Author(s)/Year	Model	Specific Topic
Chiang, Jeon and Li (2007)	DCC 8 Asian FMs	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 FMs	Effect of financial crisis on the interdepen- dence of financial and FX markets
Cheung, Fung and Tam (2008)	DCC 11 EMEAP and US	Interdependence of financial markets, Contagion risk in EMEAP region
Cho and Parhizgari (2008)	DCC 8 Asian FMs	East Asian financial contagion under DCC-GARCH
Beirne, Caporale, Ghattas and Spagnolo (2009)	MGARCH in-mean 41 FMs: Asia, Latin America, Middle East	Global and Regional volatility spillover
Frank, Gonzalez-Hermosillo and Hesse (2009)	DCC GARCH and Hesse	Transmission of Liquitity Schocks: Evidence from 2007 Subprime Crisis
Munoz, Marquez and Chulia (2010)	TSFA, DCC 19 FMs: North America, Europe, Asia	Asian financial crisi, Dot-com crisis, Global financial crisis
Yiu, Ho and Choi (2010)	PCA, ADCC 11 EMEAP and US	Dynamic correlation analysis of financial contagion in Asian markets in global financial turnoil
Naoui, Khemiri and Kiouane (2010)	DCC 10 FMs: Asia, Latin America and US	Sub-prime crisis 2007
Kenourgios, Samitas and Paltalidis (2011)	AG-DCC, copula DCC BRICS, UK, US	Five recent financial crisis
Marçal, Valls Pereira, Martin and Nakamura (2011)	9 FMs; Argentina, Brazil, South Korea, US, Singapore, Malaysia, Mexico, Japan	Evaluating of contagion or interdependence in the financial crisis of Asia and Latin American, considering macroeconomics fundamentals
Kazi, Guesmi and Kaabia (2011)	DCC 17 FMs: OECD countries	Contagion effect of Finanical Crisis on OECD Stock Markets
Celik (2012)	DCC GARCH 8 FMs: Japan. Malaysia, Denmark, Canada, China, Australia, Brazil	Contagion Effect on emerging markets. The evidence of DCC-GARCH model
Chittedi (2015)	DCC GARCH India and US	Financial Crisis and Contagion Effects to Indian Stock Market: DCC-GARCH Analysis

Consequently, this paper will confirm the hypothesis of financial contagion during the technologybubble, if structural breaks are identified. In contrast to previous papers, like Anderson et al. (2010), Koller, Goedhart, and Wessels (2010), Phylaktis and Xia (2009), 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 definitions

As mentioned before, many papers focus on the explication, proof, and analysis of market mispricing. Particularly, many well-known scientists—leading by (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.

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.



Figure 1. NASDAQ Composite and Compound Returns of NASDAQ 1990–2005.

3.2. Technology-bubbles and their development

The following section 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 technologybubble 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 (2013) 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 Ofek and Richardson (2001), Xiong (2013) and Brunnermeier and Nagel (2005) 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. American and European indices 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.

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.

This date was identified using (Phillips et al., 2013) methodology and Figure 3 shows the Critical Value for the test statistics. As can be seen the date of the maximum value for the test statistics is 9th of March 2000.

3.3. 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 Shefrin and Statman (1984) 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 & Schueßler, 2011).

3.3.1. 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.



Figure 3. Phillips et al. (2013) critcial values.

Figure 4. Normalized stock

market indices.



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 Long, Shleifer, Summers, and Waldmann (1990a) shows that rational arbitragers intensify more than dissolve the price volatilities under certain circumstances. The model implies three investor types, based on Long 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 & Naoui, 2011) showed that rational investors tend to destabilize than to stabilize

Table 2. Descr	iptive stat	istics of co	mpounded	l stock mar	ket returns		
	Mean	Min	Max	Std. dev.	Kurtosis	Skewness	Jarque-Bera
Panel A: Descripti	ve statistic	1			1		
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	0.01386	8.23300	-0.06048	6793.79
IXIC	0.00043	-0.10168	0.13255	0.01522	9.01064	-0.08929	8966.10
Panel B: Summar	y of uncondi	tional correlat	ion matrix of	f compounded	l 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	0.42028	
IXIC						1.00000	
	FPE	AIC	HQIC	S			
Dot-Com—July 1998–Ocotber 2001							
	FTSE100	DAX	INDU	SP500	SXXE	IXIC	
FTSE100	1	0.7383	0.4165	0.4392	0.8095	0.3713	
DAX		1	0.4802	0.4983	0.8950	0.4549	
INDU			1	0.9158	0.4412	0.6408	
SP500				1	0.4712	0.84063	
SXXE					1	0.4301	
IXIC						1	

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

Table 3. 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

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 Long, Shleifer, Summers, and Waldmann (1990b).

3.3.2. Other behavioral 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 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 Bondt 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.

Table 4. Orde	r selection						
Sample: 5–5,951			N obs: 5,947				
lag	LL	LR	df	FPE	AIC	HQIC	SBIC
0	127,377.0			1.00E-26	-42.8352	-42.8329	-42.83
1	128,188.0	1,622.9	36	7.54E-27*	-43.1318 *	-43.0796	-43.05 *
2	128,289.0	202.96	36	7.60E-27	-43.1180	-43.0875 *	-43.03
3	128,367.0	154.16	36	7.55E-28	-43.0960	-43.0873	-43.03
4	128,397.0	60.263 *	36	7.56E-28	-43.1299	-43.0712	-42.96
Endogenous: FT	SE100 DAX INI	DU SP500 SXX	KE IXIC				

Exogenous: constant

Table 5. Dyn	amic conditio	nal correlati	on (DCC)				
DCC	log likelihood	134,365.0					
		Coef.	Std. Err	t-stat	p-value	[95% Conf	. Interval]
GARCH_ FTSE100	arch L1	0.0637757	0.003932	16.22	0.0000	0.0560691	.0714823
	garch L1	0.9284701	0.0043591	212.99	0.0000	0.9199264	0.9370139
	_cons	1.32E-06	1.69E-07	7.79	0.0000	9.85E-07	1.65e-06
GARCH_DAX	arch L1	0.0656224	0.0035701	18.38	0.0000	0.0586252	0.0726196
	garch L1	0.9247539	0.0039471	234.29	0.0000	0.9170178	0.93249
	_cons	2.62E-06	2.56E-07	10.23	0.0000	2.12E-06	3.12e-06
GARCH_INDU	arch L1	0.048682	0.0027587	17.65	0.0000	0.0432751	0.0540889
	garch L1	0.9431361	0.003256	289.66	0.0000	0.9367545	0.9495178
	_cons	9.69E-07	1.09E-07	8.86	0.0000	7.55E-07	1.18e-06
GARCH_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	0.9501286
	_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	0.0758664
	garch L1	0.9229969	0.0041044	224.88	0.0000	0.9149524	0.9310413
	_cons	2.32E-06	2.33E-07	9.98	0.0000	1.87E-06	2.78e-06
GARCH_IXIC	arch L1	0.0501756	0.0029842	16.81	0.0000	0.0443267	0.0560245
	garch L1	0.9441076	0.0033041	285.74	0.0000	0.9376317	0.9505834
	_cons	1.24E-06	1.55E-07	7.99	0.0000	9.33E-07	1.54e-06
	corr(FTSE100, DAX)	0.821963	0.0180374	45.57	0.0000	0.7866103	0.8573157
	corr(FTSE100, INDU)	0.5322808	0.0386091	13.79	0.0000	0.4566083	0.6079532
	corr(FTSE100, SP500)	0.5233292	0.0389469	13.44	0.0000	0.4469947	0.5996637
	corr(FTSE100, SXXE)	0.8531915	0.0148766	57.35	0.0000	0.824034	0.882349
	corr(FTSE100, IXIC)	0.478945	0.0412931	11.6	0.0000	0.398012	0.5598779
	corr(DAX, INDU)	0.5584386	0.0367332	15.2	0.0000	0.4864428	0.6304344
	corr(DAX, SP500)	0.550688	0.0370227	14.87	0.0000	0.4781249	0.6232511
	corr(DAX, SXXE)	0.9538348	0.0056143	169.89	0.0000	0.9428309	0.9648387
	corr(DAX, IXIC)	0.5290064	0.0384327	13.76	0.0000	0.4536796	0.6043332
	corr(INDU, SP500)	0.9681275	0.0034649	279.41	0.0000	0.9613365	0.9749185
	corr(INDU, SXXE)	0.5657075	0.0364892	15.5	0.0000	0.49419	0.6372249
	corr(INDU, IXIC)	0.8703043	0.013504	64.45	0.0000	0.8438368	0.8967717
	corr(SP500, SXXE)	0.5590736	0.0367229	15.22	0.0000	0.4870981	0.6310491
	corr(SP500, IXIC)	0.9308737	0.0076038	122.42	0.0000	0.9159706	0.9457769

(Continued)

Table 5. (Co	ntinued)						
DCC	log likelihood	134,365.0					
		Coef.	Std. Err	t-stat	p-value	[95% Conf	. Interval]
	corr(SXXE, IXIC)	0.5248839	0.0387751	13.54	0.0000	0.4488861	0.6008818
Adjustment	λ1	0.0185426	0.0007269	25.51	0.0000	0.0171179	0.0199674
	λ ₂	0.9763659	0.0009138	1068.47	0.0000	0.9745749	0.9781569

Another aspect that occurs during a bubble is the Narrow Framing, researched and introduced by Barberies and Thaler (2003) and Barberis, Huang, and Thaler (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 (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) and Kugler and Hanusch (1992).

4. Methodology and empirical specification

In following section, the data-set will be analyzed as well as the 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 the US, the UK, and Germany (All indices are shown in Figure 7). The reason for choosing this group of countries is the idea of having three representatives for American and as well three for European markets. The daily data are collected over the period from 1 December 1990 to 31 December 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. 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).

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:

$$r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right),\tag{1}$$

Table 6. Constar	nt contional correlatio	n (CCC)						
CCC	log likelihood	132433.3						
			Coef.	Std. Err	t-stat	p-value	[95% Coi	nf. Interval]
GARCH_FTSE100	arch L1		0.0566933	0.0043693	12.98	0.0000	0.0481296	0.065257
	garch L1		0.9170612	0.0063143	145.24	0.0000	0.9046854	0.9294369
	_cons		2.36E-06	2.72E-07	8.69	0.0000	1.83E-06	2.90e-06
GARCH_DAX	arch L1		0.0567807	0.0038654	14.69	0.0000	0.0492047	0.0643568
	garch L1		0.912734	0.0055912	163.24	0.0000	0.9017754	0.9236926
	_cons		4.71E-06	4.16E-07	11.31	0.0000	3.89E-06	5.52e-06
GARCH_INDU	arch L1		0.0488243	0.003367	14.5	0.0000	0.0422251	0.0554235
	garch L1		0.9230098	0.0052205	176.8	0.0000	0.9127778	0.9332419
	_cons		2.33E-06	2.20E-07	10.59	0.0000	1.90E-06	2.76e-06
GARCH_SP500	arch L1		0.0487081	0.0029914	16.28	0.0000	0.0428451	0.0545712
	garch L1		0.9252955	0.0044994	205.65	0.0000	0.9164769	0.9341142
	_cons		2.25E-06	1.93E-07	11.66	0.0000	1.87E-06	2.62e-06
GARCH_SXXE	arch L1		0.0572276	0.003592	15.93	0.0000	0.0501874	0.0642677
	garch L1		0.9122415	0.0053578	170.26	0.0000	0.9017403	0.9227427
	_cons		4.09E-06	3.57E-07	11.44	0.0000	3.39E-06	4.79e-06
GARCH_IXIC	arch L1		0.0564031	0.0041244	13.68	0.0000	0.0483193	0.0644868
	garch L1		0.9201043	0.0056235	163.62	0.0000	0.9090824	0.9311262
	_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	0.7330547
	corr(FTSE100, INDU)		0.4836002	0.0099302	48.7	0.0000	0.4641374	0.5030629
	corr(FTSE100, SP500)		0.4890056	0.0098663	49.56	0.0000	0.4696681	0.5083431
	corr(FTSE100, SXXE)		0.7949716	0.0048163	165.06	0.0000	0.7855319	0.8044113
	corr(FTSE100, IXIC)		0.4502268	0.0103378	43.55	0.0000	0.4299651	0.4704885
	corr(DAX, INDU)		0.500551	0.009725	51.47	0.0000	0.4814903	0.5196117
	corr(DAX, SP500)		0.5019937	0.0097125	51.69	0.0000	0.4829576	0.5210298
	corr(DAX, SXXE)		0.9017632	0.0024279	371.42	0.0000	0.8970046	0.9065218
	corr(DAX, IXIC)		0.4781202	0.0100103	47.76	0.0000	0.4585003	0.4977401
	corr(INDU, SP500)		0.9507579	0.0012527	758.94	0.0000	0.9483026	0.9532132
	corr(INDU, SXXE)		0.5075809	0.009623	52.75	0.0000	0.4887201	0.5264416
	corr(INDU, IXIC)		0.7935335	0.0048023	165.24	0.0000	0.7841211	0.8029458
	corr(SP500, SXXE)		0.5133537	0.0095535	53.73	0.0000	0.4946292	0.5320783
	corr(SP500, IXIC)		0.8832718	0.0028555	309.32	0.0000	0.877675	0.8888685
	corr(SXXE, IXIC)		0.4854565	0.0099103	48.99	0.0000	0.4660327	0.5048804

where $P_{i, t}$ and $P_{i, t-1}$ are the closing prices for day t and t - 1, respectively.

Figure 6 indicates those compounded market returns and identifies some clusters, especially in times of crisis and bubbles. As Figure 6 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.

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

Table 7. Varying c	onditional correlation (V	cc)						
VCC	log likelihood	134,214.6						
			Coef.	Std. Err	t-stat	<i>p</i> -value	[95% Conf. Inte	irval]
GARCH_FTSE100	arch L1		0.0544271	0.0035372	15.39	0.0000	0.0474943	0.0613599
	garch L1		0.9350071	0.004138	225.96	0.0000	0.9268968	0.9431174
	cons		1.10E-06	1.46E-07	7.49	0.0000	8.09E-07	1.38e-06
GARCH_DAX	arch L1		0.0576292	0.003266	17.65	0.0000	0.0512281	0.0640304
	garch L1		0.9293052	0.003799	244.62	0.0000	0.9218593	0.9367512
	cons		2.14E-06	2.18E-07	9.84	0.0000	1.72E-06	2.57e-06
GARCH_INDU	arch L1		0.0421658	0.0025885	16.29	0.0000	0.0370924	0.0472393
	garch L1		0.9482422	0.0031278	303.17	0.0000	0.9421119	0.9543726
	cons		8.14E-07	9.35E-08	8.7	0.0000	6.31E-07	9.97e-07
GARCH_SP500	arch L1		0.0423039	0.0023652	17.89	0.0000	0.0376682	0.0469397
	garch L1		0.948913	0.0027878	340.39	0.0000	0.9434491	.9543769
			8.00E-07	8.36E-08	9.56	0.0000	6.36E-07	9.64e-07
GARCH_SXXE	arch L1		0.059196	0.0032934	17.97	0.0000	0.052741	0.065651
	garch L1		0.9291395	0.0038433	241.75	0.0000	0.9216067	0.9366723
	cons		1.84E-06	1.93E-07	9.55	0.0000	1.46E-06	2.22e-06
GARCH_IXIC	arch L1		0.045179	0.0029277	15.43	0.0000	0.0394407	0.0509173
	garch L1		0.9472675	0.0033381	283.78	0.0000	0.940725	.9538101
	cons		1.11E-06	1.41E-07	7.82	0.0000	8.29E-07	1.38e-06
	corr(FTSE100, DAX)		0.8283366	0.0141773	58.43	0.0000	0.8005496	0.8561237
	corr(FTSE100, INDU)		0.5972023	0.0278819	21.42	0.0000	0.5425548	0.6518497
	corr(FTSE100, SP500)		0.5944924	0.0279476	21.27	0.0000	0.5397161	0.6492687
	corr(FTSE100, SXXE)		0.8797772	0.0112918	77.91	0.0000	0.8576458	0.9019087
	corr(FTSE100, IXIC)		0.5510388	0.0298334	18.47	0.0000	0.4925664	0.6095113
	corr(DAX, INDU)		0.6245571	0.0265202	23.55	0.0000	0.5725785	0.6765357
	corr(DAX, SP500)		0.6244122	0.0265098	23.55	0.0000	0.572454	0.6763704
	corr(DAX, SXXE)		0.9515905	0.0045002	211.46	0.0000	0.9427704	0.9604107
	corr(DAX, IXIC)		0.6110261	0.0277104	22.05	0.0000	0.5567148	0.6653374
	corr(INDU, SP500)		0.9798125	0.0024536	399.34	0.0000	0.9750035	0.9846214
	corr(INDU, SXXE)		0.6262268	0.0261806	23.92	0.0000	0.5749138	0.6775398
	corr(INDU, IXIC)		0.8951593	0.0100909	88.71	0.0000	0.8753814	0.9149372
	corr(SP500, SXXE)		0.6291264	0.026123	24.08	0.0000	0.5779263	0.6803265
	corr(SP500, IXIC)		0.9442859	0.0057635	163.84	0.0000	0.9329896	0.9555823
	corr(SXXE, IXIC)		0.6000664	0.0277685	21.61	0.0000	0.5456412	0.6544916
Adjustment	λ_1		0.0096982	0.0006687	14.5	0.0000	0.0083875	0.0110088
	λ_{2}		0.9857504	0.001007	978.88	0.0000	0.9837767	0.9877241

Table 8. Dynamic	conditional correlation	(DCC)—DotCom						
			Coef.	Std. Err	t-stat	p-value	[95% Conf. Int	erval]
GARCH_FTSE100	arch L1	- <u>·</u>	04813	0.01168	4.12000	0.00000	0.0252421	0.071027
	garch L1	0	92158	0.02165	42.58000	0.00000	0.8791574	0.9640074
	cons	ō	00001	0.00000	2.31000	0.02100	7.58E-07	9.33E-06
GARCH_DAX	arch L1	0	05385	0.00977	5.51000	0.00000	0.0347031	0.0729936
	garch L1	0	92078	0.01626	56.64000	0.00000	0.8889207	0.9526409
		0	00001	0.00000	2.92000	0.00400	2.25E-06	0.0000115
GARCH_INDU	arch L1	Ō	05979	0.01194	5.01000	0.00000	0.0363957	0.0831853
	garch L1	0	85660	0.02902	29.52000	0.00000	0.79973	0.9134672
	cons	0	00001	0.00000	3.71000	0.0000	6.18E-06	0.0002
GARCH_SP500	arch L1	Ō	06688	0.01054	6.35000	0.00000	0.0462315	0.0875359
	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
GARCH_SXXE	arch L1	0.0	491893	0.0078001	6.31	0	0.0339015	0.0644772
	garch L1	0.0	933348	0.0124432	75.01	0	0.9089598	0.9577361
	cons	4.4	46E-06	1.65E-06	2.7	0.007	1.23E-06	7.70E-06
GARCH_IXIC	arch L1	0.0	910504	0.0159422	5.71	0	0.0598043	0.1222965
	garch L1	0.8	756518	0.0207303	42.24	0	0.8350212	0.9162824
	_cons	0.0	000194	5.22E-06	3.72	0	9.21E-06	0.0000297
	corr(FTSE100, DAX)	0.7/	033607	0.0286741	24.53	0	0.6471604	0.759561
	corr(FTSE100, INDU)	0.4	.220634	0.046705	9.04	0	0.3305233	0.5136036
	corr(FTSE100, SP500)	0.4	594516	0.0447188	10.27	0	0.3718043	0.5470989
	corr(FTSE100, SXXE)	0.7	819671	0.0220657	35.44	0	0.7387191	0.8252151
	corr(FTSE100, IXIC)	0.3	807854	0.0481512	7.91	0	0.2864108	0.4751599
	corr(DAX, INDU)	0.5.	303848	0.0418188	12.68	0	0.4484214	0.6123483
	corr(DAX, SP500)	0.5	490873	0.0405044	13.56	0	0.4697002	0.6284744
	corr(DAX, SXXE)	0.8	927438	0.0113909	78.37	0	0.8704181	0.9150696
	corr(DAX, IXIC)	0.4	767012	0.0437766	10.89	0	0.3909007	0.5625017
	corr(INDU, SP500)	.6.0	120803	0.0096324	94.69	0	0.8932012	0.9309594
	corr(INDU, SXXE)	0.4	474138	0.0441592	10.74	0	0.3875875	0.5606885
	corr(INDU, IXIC)	.9.0	709701	0.03128	21.45	0	0.6096625	0.7322777
	corr(SP500, SXXE)	0.5	134809	0.0417795	12.29	0	0.4315947	0.5953672
	corr(SP500, IXIC)	0.8	615081	0.014567	59.14	0	0.8329573	0.8900588
	corr(SXXE, IXIC)	0.4	582415	0.0444068	10.32	0	0.3712058	0.5452772
Adjustment	λ_1	0.0	253714	0.0039216	6.47	0	0.0176852	0.0330576
	A ₂	0.9	340111	0.0119504	78.16	0	0.9105889	0.9574334

Table 9. Constant c	onditional correlation (C	CC)—DotCoı	n					
CCC-DotCom	log likelihood	16387.2						
			Coef.	Std. Err	t-stat	p-value	[95% Con	f. Interval]
GARCH_FTSE100	arch L1		0.0406604	0.0114597	3.55	0	0.0181999	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
GARCH_DAX	arch L1		0.0436849	0.0094803	4.61	0	0.0251038	0.0622659
	garch L1		0.9304494	0.0172803	53.84	0	0.8965805	0.9643182
	_cons		7.11E-06	2.64E-06	2.69	0.007	1.92E-06	0.0000123
GARCH_INDU	arch L1		0.0505734	0.0118154	4.28	0	0.0274156	0.0737312
	garch L1		0.8473798	0.0365116	23.21	0	0.7758183	0.9189413
	_cons		0.0000166	4.85E-06	3.43	0.001	7.15E-06	0.0000261
GARCH_SP500	arch L1		0.0591682	0.0109687	5.39	0	0.0376699	0.0806666
	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
GARCH_SXXE	arch L1		0.0386898	0.0068942	5.61	0	0.0251775	0.0522022
	garch L1		0.9405349	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
GARCH_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	0.6863683	0.7527731
	corr(FTSE100, INDU)		0.4141423	0.0290111	14.28	0	0.3572816	0.4710029
	corr(FTSE100, SP500)		0.4467607	0.0280144	15.95	0	0.3918534	0.5016679
	corr(FTSE100, SXXE)		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, SXXE)		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	0.0059619	152.87	0	0.8996938	0.9230639
	corr(INDU, SXXE)		0.4391554	0.028336	15.5	0	0.3836179	0.4946929
	corr(INDU, IXIC)		0.6583122	0.0198526	33.16	0	0.6194018	0.6972225
	corr(SP500, SXXE)		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(SXXE, IXIC)		0.4572583	0.0277682	16.47	0	0.4028336	0.5116831

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 and 90%, and the American Indices: INDU, SP500, and IXIC, have nearly 78 to 96%. The correlations between the

Table 10. Varying c	onditional correlation (V	'CC)—DotCom					
VCC—DotCom	log likelihood	16,415.15					
		Coef.	Std. Err	t-stat	p-value	[95% Conf. Interval]	
GARCH_FTSE100	arch L1	0.044671	.4 0.0115974	3.85	0	0.0219408	0.067402
	garch L1	0.923368	31 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
GARCH_DAX	arch L1	0.051854	+7 0.0107783	4.81	0	0.0307296	0.0729798
	garch L1	0.92094	+3 0.0184293	49.97	0	0.8848236	0.957065
	_cons	7.40E-06	2.67E-06	2.77	0.006	2.17E-06	0.0000126
GARCH_INDU	arch L1	0.066969	9 0.0140671	4.76	0	0.0393989	0.094541
	garch L1	0.838119	0.0340613	24.61	0	0.7713607	0.9048786
	_cons	0.000016	6 4.34E-06	3.69	0	7.53E-06	0.0000245
GARCH_SP500	arch L1	0.077049	0.0126339	6.1	0	0.0522878	0.1018118
	garch L1	0.844753	0.0229161	36.86	0	0.7998382	0.8896677
	cons	0.000015	33 3.18E-06	4.81	0	9.07E-06	0.0000216
GARCH_SXXE	arch L1	0.044547	6 0.0078917	5.64	0	0.0290802	0.060015
	garch L1	0.934201	.8 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
GARCH_IXIC	arch L1	0.101378	37 0.0186211	5.44	0	0.064882	0.1378754
	garch L1	0.860262	0.0235111	36.59	0	0.8141815	0.9063434
	cons	0.000025	6.43E-06	3.89	0	0.0000124	0.0000376
	corr(FTSE100, DAX)	0.716628	36 0.0192357	37.26	0	0.6789274	0.7543298
	corr(FTSE100, INDU)	0.428927	8 0.0323449	13.26	0	0.365533	0.4923226
	corr(FTSE100, SP500)	0.458249	0.0313423	14.62	0	0.3968194	0.5196788
	corr(FTSE100, SXXE)	0.796353	0.0146158	54.49	0	0.7677068	0.8249998
	corr(FTSE100, IXIC)	0.405241	.8 0.0330293	12.27	0	0.3405055	0.4699781
	corr(DAX, INDU)	0.496152	5 0.0303153	16.37	0	0.4367357	0.5555694
	corr(DAX, SP500)	0.520163	6 0.029428	17.68	0	0.4624858	0.5778415
	corr(DAX, SXXE)	0.89334/	·9 0.0079944	111.75	0	0.8776762	0.9090136
	corr(DAX, IXIC)	0.482836	0.0306359	15.76	0	0.4227912	0.5428815
	corr(INDU, SP500)	0.920397	14 0.0063063	145.95	0	0.9080374	0.9327575
	corr(INDU, SXXE)	0.459600	0.031595	14.55	0	0.3976753	0.5215255
	corr(INDU, IXIC)	0.683987	71 0.021553	31.74	0	0.6417441	0.7262301
	corr(SP500, SXXE)	0.498375	0.0302599	16.47	0	0.4390668	0.5576832
	corr(SP500, IXIC)	0.863260	0.0102195	84.47	0	0.8432304	0.8832899
	corr(SXXE, IXIC)	0.472959	98 0.031049	15.23	0	0.4121049	0.5338146
Adjustment	λ_1	0.117438	33 0.0325576	3.61	0	0.0536265	0.1812501
	1,2	0.075768	31 0.2598084	0.29	0.771	-0.433447	0.5849832

Table 11. Wald-test full sample	
H _o :	$\lambda_1 = \lambda_2 = 0$
ℵ ² (2) stat	5.5E + 06
<i>p</i> -value	0.0E + 00

Table 12. Wald-test DotCom					
H _o :	$\lambda_1 = \lambda_2 = 0$				
ℵ ² (2) stat	17776.8				
<i>p</i> -value	0.0E + 00				

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.

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 using ADF and PP and the test does not reject the null of stationarity, indicating that the return series are stationary.

Table 13. Dynamic conditional correlation—Full sample vs. DotCom						
DCC: Full sample						
	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.8220	0.5323	0.5233	0.8532	0.4789
DAX	0.8220	1	0.5584	0.5507	0.9538	0.5290
INDU	0.5323	0.5584	1	0.9681	0.5657	0.8703
SP500	0.5233	0.5507	0.9681	1	0.5591	0.9309
SXXE	0.8532	0.9538	0.5657	0.5591	1	0.5249
IXIC	0.4789	0.5290	0.8703	0.9309	0.5249	1
DCC: DotCom Bubble						
	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.7034	0.4221	0.4595	0.7820	0.3808
DAX	0.7034	1	0.5304	0.5491	0.8927	0.4767
INDU	0.4221	0.5304	1	0.9121	0.4741	0.6710
SP500	0.4595	0.5491	0.9121	1	0.5135	0.8615
SXXE	0.7820	0.8927	0.4741	0.5135	1	0.4582
IXIC	0.3808	0.4767	0.6710	0.8615	0.4582	1
DCC: 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



Figure 7 depicts the scatter 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.

5. Model selection

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 matrix, 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.

Figure 7. Scatter plot every indices against each other.



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

$$\mathbf{r}_{t} = \mathbf{\mu} + \sum_{s=1}^{p} \Phi_{s} \mathbf{r}_{t-s} + \varepsilon_{t} \text{ for } t = 1, \dots, T,$$

$$\varepsilon_{t} | I_{t-1} \sim N(0, H_{t}), \qquad (2)$$

where \mathbf{r}_t is a 6 imes 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_t is a 6×1 vector of i.i.d errors:

$$\boldsymbol{\varepsilon}_{t} = (\varepsilon_{\text{FTSE100},t}, \varepsilon_{\text{DAX},t}, \varepsilon_{\text{INDU},t}, \varepsilon_{\text{SP500},t}, \varepsilon_{\text{SXXE},t}, \varepsilon_{\text{IXIC},t})' = \boldsymbol{H}_{t}^{1/2} \mathbf{z}_{t},$$
(3)
with $\mathbf{z}_{t} \sim N(\mathbf{0}, \boldsymbol{I}_{6}).$

 H_{t} is the conditional covariance matrix that is

$$H_t = E(\varepsilon_t \varepsilon_t' | I_{t-1}).$$
(4)

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

$$H_t = D_t R_t D_t, (5)$$

where $D_t = diag(\sigma_{FSTE100,t}, \sigma_{DAX,t}, \sigma_{INDU,t}, \sigma_{SP500,t}, \sigma_{SXXE,t}, \sigma_{IXIC,t})$ is a 6 × 6 diagonal matrix of time varying standard deviations from univariate GARCH models, for example:

$$\sigma_{i,t}^{2} = \omega_{i} + \alpha_{i} \varepsilon_{i,t-1}^{2} + \beta_{i} \sigma_{i,t-1}^{2}, \tag{6}$$

Table 14. Constant conditional correlation: Full sample vs. DotCom						
CCC: Full Sample						
	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.7208	0.4836	0.4890	0.7950	0.4502
DAX	0.7208	1	0.5006	0.5020	0.9018	0.4781
INDU	0.4836	0.5006	1	0.9508	0.5076	0.7935
SP500	0.4890	0.5020	0.9508	1	0.5134	0.8833
SXXE	0.7950	0.9018	0.5076	0.5134	1	0.4855
IXIC	0.4502	0.4781	0.7935	0.8833	0.4855	1
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
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

for *i* = FTSE100, DAX, INDU, SP500, SXXE, IXIC, and the time varying conditional correlation matrix is defined by:

$$R_t = \{\rho_{i,j,t}\}.\tag{7}$$

In order to obtain the DCC-GARCH model, two steps have to be taken. The first one is to estimate the univariate GARCH model for each asset. The second stage is to define the vector of standardized residuals, $\eta_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}}$ to develop the DCC correlation specification:

$$R_{t} = \left[\operatorname{diag}(\sqrt{q_{11}}, \dots, \sqrt{q_{66}}) \right] Q_{t} \left[\operatorname{diag}(\sqrt{q_{11}}, \dots, \sqrt{q_{66}}) \right], \tag{8}$$

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

$$Q_{t} = (1 - \theta_{1} - \theta_{2})\widetilde{Q} + \theta_{1}\eta_{t-1}\eta_{t-1}' + \theta_{2}Q_{t-1}.$$
(9)

The parameters θ_1 and θ_2 are positive, $\theta_1 \ge 0$ and $\theta_2 \ge 0$ and, therefore $\theta_1 + \theta_2 < 1$. These parameters which are the same for every pair, capture the effect of previous shocks and previous DCC on current dynamic correlation. \widetilde{Q} is the sample unconditional variance–covariance matrix of all standardized residuals $\eta_{i,t}$ with a correlation estimation like following:

Table 15. Varying conditional correlation (VCC): Full sample vs. DotCom						
VCC: Full sample						
	FTSE100	DAX	INDU	SP500	SXXE	IXIC
FTSE100	1	0.8283	0.5972	0.5945	0.8798	0.5510
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	0.9443
SXXE	0.8798	0.9516	0.6262	0.6291	1	0.6001
IXIC	0.5510	0.6110	0.8952	0.9443	0.6001	1
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	0.4596	0.6840
SP500	0.4582	0.5202	0.9204	1	0.4984	0.8633
SXXE	0.7964	0.8933	0.4596	0.4984	1	0.4730
IXIC	0.4052	0.4828	0.6840	0.8633	0.4730	1
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

$$\rho_{i,j,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}.$$
(10)

As Aielli (2013) pointed out in the DCC model the choice of \widetilde{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 Engle and Sheppard (2001) DCC model, except the correlation Q_r :

$$Q_{t} = (1 - \theta_{1} - \theta_{2})\widetilde{Q} + \theta_{1}\eta_{t-1}^{*}(\eta_{t-1}^{*})' + \theta_{2}Q_{t-1} \text{ where } \eta_{t}^{*} = \operatorname{diag}(Q_{t})^{\frac{1}{2}}\eta_{t}.$$
 (11)

5.1. 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) for the lag length selection.

The "*" indicates the optimal lag. The HQIC has chosen a model with two lags, whereas FPE, AIC and even the SBIC have selected a model with only one lag. The conditional variance equation for each indices. A GARCH(1,1) will be used. Table 5 shows the DCC estimation with GARCH(1,1)

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 DCCs 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 Tables 6 and 7.

The same methodologies of the DCC, CCC, and VCC are used for the specific time frame of the DotCom, which is illustrated in Tables 8–10.

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.

An interesting finding can be even seen in Tables 13–15. 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, the null hypothesis 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.



Figure 8. Estimated dynamic correlation coefficients.







Figure 10. Estimated dynamic correlation coefficients DotCom.



Figure 8 visualizes the computed individually DCC plots for pairwise countries with the different contagion source countries.

The breakpoint 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 8. The time frame is July 1998 to October 2001.

Having estimated the DCC model, the conditional variance is forecasted for the next 50 time periods into the future. Figure 9 shows the result of those forecasts. From those conditional variances, one can see the impact of crisis to the different stock markets. As Figure 10 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 11 illustrates this specific time frame.

6. Summary and conclusions

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 comovements 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.

The empirical findings showed that the American and European (as well separately UK 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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Note

1. We are not going to present the econometrics methods used to detect the time of the bubble which can be seen in the Phillips et al. (2013, 2011) papers. We will used they methodology to identify the period of the bubble as will be seen in Figure 3.

References

- Abreu, D., & Brunnermeier, M. K. (2003). Bubbles and crashes. Econometrica, 71, 173–204.
- Aielli, G. P. (2013). Dynamic conditional correlation: On properties and estimation. *Journal of Business & Economic Statistics*, 31(3), 282–299.

Anderson, K. P., Brooks, C., & Katsaris, A. (2010). Speculative bubbles in the s &p P 500: was the tech bubble confined to the tech sector? *Journal of Empirical Finance*, 17(3), 345–361.

- Armada, M. J. R., Leitão, J., & Lobão, J. (2011). The contagion effects of financial crisis on stock markets: what can we learn from a cointegrated vector autoregressive approach for developed countries. *Revista Mexicana de Economia Y Finanzas*, 6, 29–53.
- Arrow, K. (1982). Risk perception in psychology and economics. Economic Inquiry, 20(1), 1–9.
- Arruda, B. P., & Pereira, P. L. V. (2013). Analysis of the volatility's dependency structure during the saubprime crisis. Appleid Economics, 45(36), 5031–5045.
- Aschinger, G. (1991). Theorie der spekulativen blasen. Wirtschaftsiwssenschatftliches. Studium, 20(6), 270–284.
- Azad, A. S. M. Sohel. (2009). Efficiency, cointegration and contagion in equity markets: Evidence from China, Japan and South Korea. Asian Economic Journal, 23(1), 93118.
- Bae, K.-H., Karolyi, G. A., & Stulz, R. M. (2003). A new approach to measuring financial contagion. *Review of Financial Studies*, 16(3), 717–763.
- Barberies, N., & Thaler, R. (2003). A survey of behavioral finance. M. H. In, G. M. Constantinides, & R. Stulz (Eds.), Handbook of Economic of Finance, volume 1 chapter 18 (pp. 1053–1128). Amsterdam: Elsevier.

- Barberis, N., Huang, M., & Thaler, R. (2006). A model of investor sentiment individual preference, monetary gambles and stock market participation: A case for narrow framing. *Americna Economic Review*, 96(4), 1069–1090.
- Belhoula, M., & Naoui, K. (2011). Herding and positive feedback trading in american stock market: a two co-directional behavior of investor. International Journal of Business and Management, 6(9), 244–252.
- Blanchard, O. J. (1982). Bubbles, rational expectations and financial markets (Technical report, NBER Working Paper Series 945).
- Bollerslev, T. (1990). Modemodel the coherence in short-run nominal exchange rates: A multivariate generalized arch model. *Review of Economics and Statistics*, 72(3), 498–505.
- Bondt, W. F. D. (1998). Behavioral economics: A portrait of the individual investor. *European Economic Review*, 42(3–5), 831–844.
- Bondt, W. F. D., & Forbes, W. P. (1999). Herding in analyst earnings forecasts: Evidence from the United Kingdom. European Financial Management, 5(2), 143–163.
- Brunnermeier, M. K., & Nagel, S. (2005). Hedge funds and the technology bubble. *Journal of Finance*, 59(8), 2013–2040.
- Carlos, A., Neal, L., & Wandschneider, K. (2006). Dissecting the anatomy of exchange alley: The dealings of stock jobbers during and after the south sea bubble (Technical report, University of Colorado Working paper).
- Cho, J. H., & Parhizgari, A. M. (2008). East asian financial contagion under dcc-garch. *International Journal of Banking and Finance*, 6(1), 17–30.
- Darbar, S. M., & Deb, P. (1997). Co-movements in international equity markets. *Journal of Financial Research*, 20(3), 305–322.
- de P Filleti, J., Hotta, L. K., & Zevallos, M. (2008). Analysis of contagion in emerging markets. *Journal of Data Science*, 6, 601–626.
- Engle, R.F., & Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate garch (Technical report, NBER Working Paper No. 8554).
 Fama, E. (1965). The behavior of stock-market prices. The

Journal of Business, 38(1), 34–105.

- Fama, E. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*(2), 383–417.
- Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, 57(5), 2223–2261.
- Garber, P. M. (1990). Famous first bubbles. Journal of Economics Perspectives, 4(2), 35–54.
- Gurkaynar, R. S. (2008). Econometric tests of asset price bubbles: taking stock. *Journal of Economic Surveys*, 22(1), 166–186.
- Hirshleifer, D., & Teoh, S. H. (2009). Thought and behavior contagion in capital markets. In T. Hens & K. Schenk-Hoppe (Eds.), Handbook of financial markets: Dynamics and evolution chapter 1 (pp. 1–46). Amsterdam: North-Holland.
- Horta, P., Medes, C., & Vierra, I. (2008). Contagion effects of the us subprime crisis on developed countries (Technical report, CEFAGE-UE Working Paper No. 8).
- Ionescu, G. H., Ungureanu, D. M., Vilag, R. D., & Stoia, F. B. (2009). Financial contagion and investors behavior. Annales Universitatis Apulensis Series Oeconomica.

Jarchow, H.-J. (1997). Rationale wechselkurserwartungen, devisenmarkteffizienz und spekulative blasen. Wirtschaftswissenschaftliches Studium, 26, 509–516.

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- Kaminsky, G. L., Reinhart, C., & Vegh, C. A. (2003). The unholy trinity of financial contagion (Technical report, NBER Working Paper No. 10061).
- Karolyi, G. A., & Stulz, R. M. (1996). Why do markets move together? An investigation of U.S.-Japan stock return co-movements. *Journal of Finance*, 51(3), 951–986. Keynes, J. M. (1935). The General Theory of Employment,
- Interest, and Money. New York: Harcourt, Brace & World. Kindleberger, C. P. (1978). Economic Response: Comparative
- Studies in Trade, Finance, and Growth. Cambridge: Harvard University Press.
- Kindleberger, C. P., & Aliber, R. Z. (2005). Manias, Panics, and Crashe. Hoboken, NJ: John Wiley & Son.
- Koller, T., Goedhart, M., & Wessels, D. (2010). Valuation: Measuring and managing the value of companies. Hoboken, NJ: Wiley Finance Series.
- Kugler, F., & Hanusch, H. (1992). Psychologie des aktienmarktes in dynamischer betrachtung: Entstehung und zusammenbruch spekulativer blasen (Technical report, Volkswirtschaftliche Diskussionsreihe No. 77).
- Long, J. B. D., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990a). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4), 703–738.
- Long, J. B. D., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990b). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, 45(2), 379–395.
- Marçal, E. F., Pereira, P. L. V., Martins, D. M. L., & Nakamura, W. T. (2011). Evaluation of contagion or interdependence in the financial crises of asia and latin america, considering the macroeconomic fundamentals. *Applied Economics*, 43(19), 2365–2379.
- Nguyen, T., & Schueßler, A. (2011). Behavioral finance als neues erklaerungsansatz fuer "irrationales" anlegerverhalten (Technical report, Diskussionpaper No. 33).
- Ofek, E. & Richardson, M. (2001). Dotcom mania: The rise and fall of internet stock prices. *The Journal of Finance, LVII*, *I*(3), 1113–1137.
- O'Hara, M. (2008). Bubbles: Some perspectives (and loose talk) from history. Review of Financial Studies, 21(1), 11–17.
- Parhizgari, A. M., Dandapani, K., & Bhattacharya., A., (1994). Global market place and causality. *Global Finance Journal*, 5(1), 121–140.
- Pelletier, D. (2006). Regime switching for dynamic correlations. Journal of Econometrics, 131, 445–473.

Pericolo, M., & Sbracia, M. (2001). A primer on financial contagion (Technical report, Bank of Italy Working paper).

- Phillips, P. C. B., Shi, S.-P., & Yu, J. (2013). Testing for multiple bubbles: Historical episodes of exuberande and collpase in the s &p500 (p. 1914). Cowles Foundation Discussion Paper Number: Technical report.
- Phillips, P. C. B., Wu, Y., & YU, J., (2011). Explosive behavior in the 1990s nasdaq: When did exuberance escalate asset values? International Economic Review, 52(1), 201–226.
- Phylaktis, K. & Xia, L. (2009). Equity market co-movement and contagion: A sectorial perspective. *Financial Management*, 38(2), 381–409.
- Ross, S. A. (2005). *Neoclassical Finance*. Princeton: Princeton University Press.
- Rotta, P. N., & Pereira, P. L. V. (2016). Analysis of contagion from the dynamic conditional correlation model with markov regime switching. *Applied Economics*, 48(25), 2367–2382. Scherbina, A. (2013). Asset price bubbles: A selective survey.
- (Technical report, IMF Working Paper 13/45) Scherbina, A., & Schlusche, B. (2012). Asset bubbles: An
- application to residential real estate. European Financial Management, 18(3), 464–491.
- Shefrin, H. M., & Statman, M. (1984). Explaining investors preference for cash dividends. *Journal of Finance Economics*, 13(253–282).
- Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. Journal of Psychology and Financial Markets, 1(1), 49–60.
- Simon, H. A. (1979). Rational decision making in business organizations. American Economic Review, 69(4), 493–513. Tirole, J. (1982). On the possibility of speculation under rational
- expectations. Econometrica, 50(5), 1163–1181. Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business & Economic Statistics, 20(3), 351–362.
- Wald, A. (1943). Tests of statistical hypotheses concerning several parameters when the number of observations is large. *Transactions of the American Mathematical Society*, 53(3), 426–482.
- Weil, H. B. (2010). Why markets make mistakes. *Kybernetes*, 39(9/10), 1429–1451.
- Xiong, W. (2013). Bubbles, crises and heterogeneous beliefs (Technical report, NBER Working Paper No. 18905).



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