THE CONSEQUENCES OF EURONEXT INTEGRATION ON THE FRENCH, BELGIAN AND DUTCH STOCK MARKETS

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Abstract

On 22 September 2000, the French, Belgian and Dutch stock exchanges merged and formed the Euronext N.V., the first pan-European exchange. The creation of Euronext was a response to changes in the political and economic environment in Europe. The benefits to market participants are easier access to a wider range of financial products, increase in liquidity and lower transaction costs. Indeed, since its incorporation, Euronext has the second largest capitalization in Europe.

The aim of this thesis is to investigate the consequences of Euronext integration on the French, Belgian and Dutch stock markets. It raises two questions: 1. has the merger improved the information efficiency of the markets; and 2. has the level of integration between the markets increased following the incorporation of Euronext? The study uses daily prices for the markets' main indices for the period 01/01/1990 to 10/12/2010. The original sample is divided into three periods: pre-integration, integration and post-integration period. Two types of returns are computed: log-returns and excess returns. A dummy variable and a control variable, the German main index DAX, are included in the analysis to account for the effect of the introduction of the Euro.

Unit root and stationarity tests show that prices series are integrated of the first order and that the returns series are stationary. Moreover, the volatility of returns exhibits long-memory patterns. The data generating process of all the returns series is captured with ARMA-GARCH models. The returns exhibit volatility clusters in all sub-periods. Hence, the information efficiency of the market has not increased following Euronext integration. However, GARCH models do not include an asymmetric component for the post-integration period, indicating that the returns do not display leverage effects after the creation of Euronext. Finally, a Euro dummy variable was significant only for the Belgian returns.

Cointegration tests show that the three indices experience long-run equilibrium during the integration and the post-integration periods. Moreover, the conditional correlation between the markets increases and stabilises after 2000. Overall, the evidence supports wider financial integration between these markets. However, it is difficult to

determine to what degree this change can be attributed to the creation of Euronext as opposed to the introduction of the Euro or to a combination of both. A Granger causality test shows that EMU has Granger caused market financial integration. On the other hand, a system comprised of the three indices and the control variable, DAX30, does not display long-run equilibrium for the post-integration period, highlighting the role of Euronext. These results are important for market participants.

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Author's Declaration

I certify that this thesis is entirely my own work.

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1. Introduction

1.1 Euronext

On 22 September 2000, the French, Belgian and Dutch stock exchanges merged and formed the Euronext N.V., a Dutch law holding company. The ambition of these historical exchanges, (Amsterdam is often viewed as the oldest exchange of the modern world), is to create the first pan-European exchange:

> Upon completion of Euronext's planned integration process, Euronext will be the first fully integrated, cross-border, European market for equities, bonds, derivatives and commodities. (Euronext Annual Report 2000, p.1)

The Euronext expansion continued with the inclusion of the London International Future and Options Exchange (LIFFE) in January 2002 and the Portuguese exchange Bolsa de Valores de Lisboa e Porto (BVLP) at the end of the same year. Finally, Euronext merged with the New York Stock Exchange (NYSE) to form the NYSE Euronext in 2007.

The incorporation of Euronext was a strategic move to take advantage of different changes in the competitive environment: an increased competition resulting from the globalization of the financial markets; radical changes in information and communication technology; diversification of the market participants. The changes in the European political and currency environment were also instrumental. Indeed, the company's original mission statement states:

> Euronext was created…in response to growing demand from the market, a political environment favorable to further consolidation in the European capital market and a desire to capitalize on greater liquidity and lower costs resulting from the introduction of the Euro. (Euronext Annual Report 2000, p. 1)

Euronext N.V is therefore a holding company that operates through local subsidiaries, e.g. Euronext Paris in France. It provides a single trading platform for equities and derivatives, a single order book for securities or financial products, a single clearing house and a unified settlement system. Furthermore, as there is a unique trading platform for cash securities, the trading rules of each subsidiary are harmonized: the most liquid securities are traded continuously and the other securities are traded at call auctions held twice a day. By the same logic, the trading hours were also synchronised. The national regulatory authorities continue to have power over the local subsidiaries, e.g. The Commission Bancaire et Financière for Euronext Brussels and the listing criteria can be different for each subsidiary, especially in terms of the size of the companies.

The national market indices, CAC40 for France, BEL20 for Belgium, AEX, PSI20 for Holland, continued to be calculated and disseminated as before the integration. Additionally, a new index was created to represent the Euronext list: Euronext 100, which is comprised of the 100 largest companies by market capitalization. (Euronext organisation and procedures 2002)

According to Euronext, the benefits from the merger for the market participants are easier access to a wider range of financial products, an increase in liquidity and lower transaction costs. In December 2000, just a couple of months after its incorporation, Euronext was the second exchange in Europe in terms of market capitalization of shares, directly after the London Stock Exchange and the first in terms of average trading volume in the cash market (Euronext Annual Report 2000, p.11).

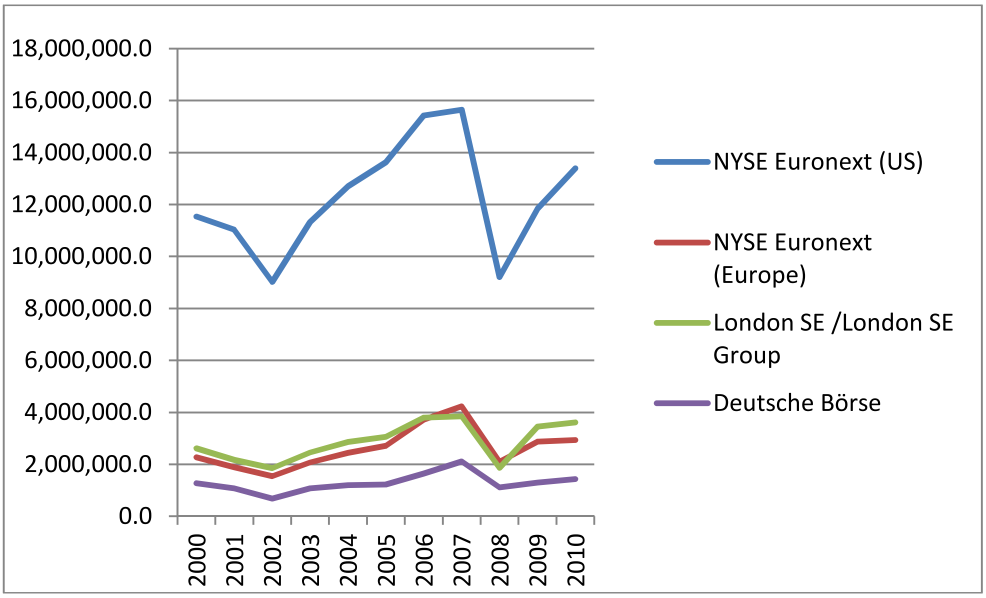
The following three figures present market indicators[2] for the New York Stock Exchange (NYSE Euronext US), the Euronext exchanges (NYSE Euronext Europe), The London Stock Exchange (London SE/London SE Group) and the German, Frankfurt based, Stock Exchange (Deutsche Börse). The London Stock Exchange merged with the Italian Borsa Italia to form the London Stock Exchange Group in 2010. However, the data of both exchanges appeared consolidated as per 2009.

Figure 1.1 shows the market capitalization for each exchange for the period 2000 to 2010. The difference between NYSE and the European exchanges is striking. Since its incorporation, Euronext has the second largest market capitalization in Europe, shadowing closely the London Stock Exchange. Indeed, Euronext achieved a higher capitalization than London in 2007 only. However, in 2009 and 2010 the gap with the now London Stock Exchange Group increased. The Deutsche Börse consistently presents the smallest capitalization of the group. It is worth noting that the financial crises of 2007 and 2008 had a remarkable impact on the capitalization of all markets: NYSE felt by 41.1%, from 15,650,832 in 2007 to 9,208,934 USD millions in 2008.

[2] Data are presented in appendix 1 (see section 10.1). Data were retrieved from the World Federation of Exchanges.

Similarly, Euronext's capitalisation decreased by 50.2%, from 4,222,679 to 2,101,745, London Stock Exchange by 51.5%, from 3,851,705 to 1,868,153 and the Deutsche Börse by 47.2%, from 2,105,197 to 1,110,579 USD millions (see appendix 1, section 10.1). Although more impressive in New York in terms of absolute number, the drop in capitalization was proportionally more important for the London and Euronext stock exchanges than for NYSE or the Deutsche Börse.

Figure 1.1: Market capitalisation in USD millions (main and parallel markets)

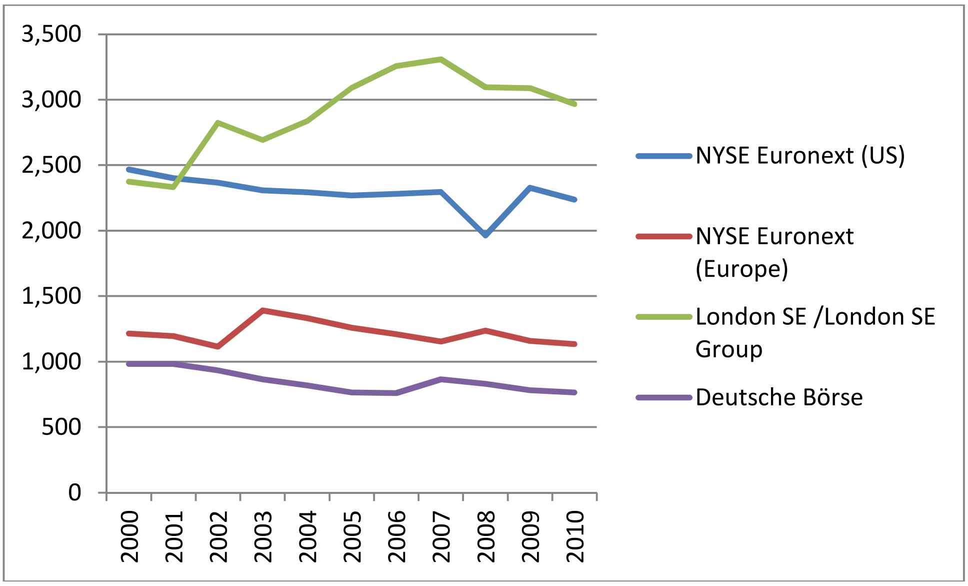


Source: adapted from World Federation of Exchanges

The total number of shares listed in the stock markets is presented in figure 1.2. Euronext is the third in importance in the group of exchanges, far from the London and New York stock exchange levels. The number of shares appears more or less stable throughout the period, roughly between 1,100 and 1,400 shares every year.

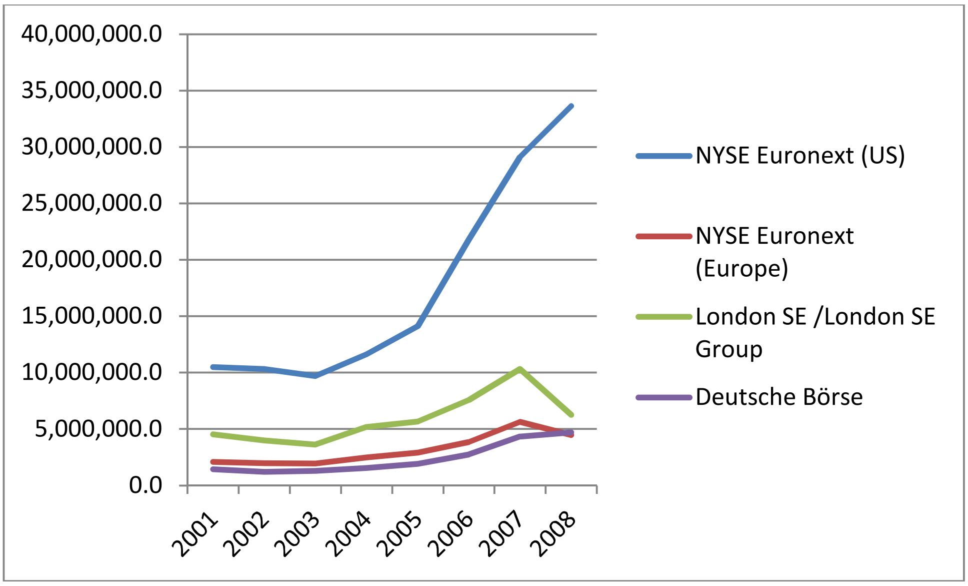
Figure 1.3 presents the value of shares traded every year. The period covered runs only from 2001 to 2008, as data were not available for Euronext for the year 2000 and the measurement of the indicator changed in 2009. Again, NYSE's performance is the most important and Euronext appears in third place, following the London Stock Exchange. The 2007-2008 financial crisis did not affect the value of share trading for NYSE, unlike Euronext and London, both of which experienced a drop in share trading.

Figure 1.2: **Number of listed companies**



Source: adapted from World Federation of Exchanges

Figure 1.3: Value of share trading in USD millions (electronic order book and negotiated deals)



Source: adapted from World Federation of Exchanges

From these market indicators, it is evident that the Euronext incorporation created the second largest stock exchange in Europe, just behind the London Stock Exchange. However, the size distance between the European and American stock exchanges remains considerable.

In the non-confidential version of a report prepared for Euronext, Pagano and Padilla (2005) presented their conclusions on the efficiency gains from the Euronext experiment. They classify these gains into two categories: cost savings and direct user benefits. The cost savings come mostly from the "elimination of duplication of costly infrastructure" (p. 3) in terms of information technology and staffing costs. The direct user benefits are:

1. a single trading platform access, allowing market professionals to save by reducing the hardware, software and skilled human capital needed to access numerous trading platforms;
2. integration allows trade in more diversified portfolios;
3. integration of national exchanges increases liquidity;
4. an increase in liquidity can reduce the price concession an investor may be forced to accept for executing a large order, and can result in lower volatility. (p.3)

Using regression analysis, the authors researched the impact of integration on liquidity for the period December 1999 to December 2004. They found a statistically significant reduction of the bid-ask spreads for the French and Belgian national stock indices (40%-48% for CAC40 and 23%-30% for BEL20) but not for the Dutch market. Also, the trading volume in each market increased significantly and the volatility of the large cap securities decreased (p. 50). The authors controlled their results for exogenous events and for common trends with other European exchanges, such as the UK or German exchanges and attributed them to the integration of Euronext.

More than a decade after the integration of Euronext, few academic papers have researched the impacts of the integration of the Pan-European exchange.

1.2 Aim of the Thesis

The aim of the present study is to investigate the consequences of the Euronext integration on the French, Belgian and Dutch stock exchanges. It does not look at the impact on the exchanges themselves, analyzing their increased efficiency in terms of operating costs, but rather focuses on the consequences for the market participants.

Essentially, it intends to answer the following research question: was the integration of the Euronext beneficial for the market participants?

To answer this broad research question, two specific research objectives are set:

1. To test the information efficiency of the French, Belgian and Dutch exchanges before and after Euronext integration.
2. To assess the level of market integration between the three exchanges before and after the Euronext integration.

Information efficiency is essential for market participants. Equal access to information ensures that the market is a fair game. Participants can make appropriate investment decisions based on equally available information and no participant can make excess returns using information not accessible to the rest of the market. The problems of fair access to information and information efficient markets are so important in finance that an entire theory, the Efficient Market Hypothesis (EMH) was developed in the 1960's. It defined the level of efficiency of a stock market as a function of the quality of information widely available in that market. EMH definitions have changed since, but it remains an important conceptual framework for testing the information efficiency of stock markets and it is adopted for the first research objective of this study.

The second research objective relates to the problem of choice of investment for market participants, and more specifically to portfolio diversification. The access to different stock exchanges from one unique platform allows the participants to choose their investment from a wide range of securities and financial products. Moreover, they can do this at a lower cost. According to Euronext (2000) and Pagano and Padilla (2005), these are direct benefits for the participants from the merger. This increased choice of investment should help participants to diversify and build efficient portfolios: modern portfolio theory posits that investing in securities which are not perfectly positively correlated allows investors to diversify the risk and to invest in efficient portfolios. However, what if the merger of the exchanges increases their integration and therefore reduces the real choice of diversification for the participants instead of increasing it? Stock market integration is an important subject in the finance literature, but unlike EMH, there is no theory dedicated to the phenomenon, just a set of definitions and numerous results from empirical research. It is an important process, seen by many as a part of economic integration, itself generated by the globalization of the economy.

The study will focus on the three original Euronext stock markets: the French, Belgian and Dutch exchanges. However, it is impossible to assess the impact of the Euronext integration on these exchanges, analysing all the securities listed in these exchanges. Hence, the main index of each exchange is used in the study: CAC40 for the French, BEL20 for the Belgian and AEX for the Dutch market. As the mode of computation of these indices was not altered by the merger, these indices are valid measurements before and after the integration.

The CAC40 index is comprised of the 40 most representative companies in terms of market capitalization and liquidity (turnover) in the Paris stock exchange. Its base value is 1,000 as of 31 December 1987.

The BEL20 includes the 20 largest companies in terms of market capitalization in the Brussels stock exchange. Its base value is 1,000 as of 30 December 1990. However, Datastream provides data for this index for the whole year 1990.

The Dutch AEX index includes the 25 most traded shares listed in the Amsterdam stock exchange. Its base is 45.38 as of 3 January 1983.

Constructed according to criteria of market capitalizations and/or liquidity, these indices are blue-chip indices for each market. They also serve as underlying for derivatives and are the bases for structured financial products.

The time window for this study is 21 years, from January 1990 to December 2010. This choice of a large window should allow for robust results and avoid biases coming from short run momentum or crashes and/or exogenous events. Moreover, it includes a long period of observations before and after the merger.

However, the integration of the Euronext was a long process. Indeed, after the incorporation of the pan-European exchange in September 2000, each subsidiary had to move its operations to a unique platform, order book, clearing and settlement system. This migration process stretched over a couple of years. For the three stock exchanges of interest in this study, the migration to the unique cash trading system was completed in October 2001 and to the cash clearing system (Clearing 21) one year later, at the end of October 2002. Based on these key dates, the original time window is divided into three sub-periods:

1. Pre-integration period: 01/01/1990 -31/08/2000,
2. Integration period: 01/09/2000-30/10/2002,
3. Post-integration period: 01/11/2002-10/12/2010.

From 1990 to 2010, the composition of each national index has changed. Some stocks were withdrawn from the indices and replaced by new ones. Other stocks split. Also, some companies merged into new ones and sometimes these were then kept in the index. However, over a long period of time, the impact of these events is tempered.

The approach adopted in this study is deductive in nature. The literature review will help transform the research objectives into testable hypotheses, design sound research methods and assist in the choice of appropriate econometric tools.

1.3 Outline of the Thesis

Overall, this thesis is comprised of a review of the literature (chapters two and three), a discussion of the methodology adopted (chapter four), a presentation of the data used (chapter five), empirical work (chapters six and seven) and a section of conclusions (chapter eight).

The scope of chapter two is to provide a theoretical framework for the first research objective. It starts with a review of the different definitions of the EMH and the arguments of the behavioural finance school. It then looks at the problem of the identification of the Data Generating Process (DGP) in finance, beginning with the problem of stationarity of an economic time series and the unit root testing procedures and concludes with a robust testing procedure. It finishes by exploring different types of nonlinear models.

In chapter three, the literature is reviewed from the perspective of the second research objective. As in the previous chapter, it starts with a review of definitions and concepts which are related to the process of market integration and its consequences on portfolios. It is then followed by a review of empirical work surveying market integration. The main tools used can be classified into two categories: the static and the dynamic models.

Chapter four presents the philosophical questions related to this research, and potential alternatives. It opens with a discussion regarding the research paradigm and research approach. It then reviews the strategy adopted and concludes with the threats to reliability and validity.

In chapter five, the data are presented. From the original closing price series, two new series are created for each index: log-returns and excess returns. The series are tested for stationarity using a robust procedure combining unit root and stationarity tests. Finally, the problem of long memory and fractional integration is tested using Hurst Rescale Range test.

Chapter six opens with the empirical work related to the first research objective: the information efficiency of the markets. Based on the findings of the literature reviewed in chapter two, hypotheses are stated and a research framework is designed in order to identify the DGP of each series for the different periods. Linear models such as random walk or general auto-regressive moving-average (ARMA) models do not capture the DGP. More complex processes, modelling both the mean and the variance of each series, are more appropriate. The choice of model is based on the iid or white noise criterion, i.e. the fact that the residuals from the estimated model are independent identical distributed, hence that there is no more information in the residuals. The potential effect of the introduction of the Euro was controlled using a dummy variable. Results presented in this chapter are therefore from univariate analysis.

Chapter seven continues the empirical work and investigates the second research objective: the market integration of the three exchanges. The findings from chapter three show the importance of the market integration process which may be a problem for proper diversification. The hypotheses tested in this chapter are therefore related to increased integration of three Euronext subsidiaries. The research design includes two types of multivariate econometric tools: one static in nature, cointegration; and one more dynamic, conditional correlation. In order to ensure robust results, two cointegration techniques are used: the Engle-Granger (EG) and the Johansen Juselius (JJ) methods. The introduction of the Euro is controlled by including a new variable, the German DAX main index, as control variable, as well as by a dummy variable. Finally, the results of the conditional correlation analysis are discussed in view of some major political and economic events.

Chapter eight presents the conclusions from all chapters, as well as possible further research paths.

The two main hypotheses examined in the thesis are the following:
H_1: The French, Belgian and Dutch stock markets are more efficient following the Euronext merger.
This hypothesis is related to the first research objective and it is addressed in chapter six.
H_2: Euronext has increased the integration of the French, Belgium and Dutch stock markets.
Related to the second research objective, this hypothesis is tested in chapter seven. It is broken down into three achievable hypotheses.
$H_{2.1}$: Euronext integration has created long-run equilibrium between the French, Belgian and Dutch markets.
$H_{2.2}$: Euronext integration has intensified information flows between the French, Belgian and Dutch markets.
$H_{2.3}$: Euronext integration has increased the correlation between the French, Belgian and Dutch markets.

1.4 Contribution of the Thesis

The Euronext integration was an important event in European and world finance: it integrated four national stock exchanges and one derivative exchange into one platform, with a unique clearing system and created the second most important exchange in Europe. However, few articles have researched the consequences of the merger for the market participants. The survey of Pagano and Padilla (2005), prepared for Euronext, focuses mainly on the cost efficiency for investors and intermediaries (p.7). Moreover, its time window, 2000 to 2004, is relatively small. As discussed above, the migration of Paris, Brussels and Amsterdam into a common cash and clearing system only ended in October 2002.

The main contribution of this thesis is therefore to address the gap in the literature. Indeed, its scope is to research the impact of Euronext integration on market participants in terms of information efficiency and market integration. Moreover, this study uses a large time window (1990-2010) allowing for robust results.

The second contribution of this thesis is the use of a wide range of univariate models and the iid criterion to identify the DGP of the market indices. The algorithm itself has been used in many papers (See for example Hsieh 1991; Willcocks 2009). However, this is the first time it is used in this context. Moreover, the algorithm is applied to two different types of return: log- and excess returns.

The third contribution of this thesis is the joint use of a "static" multivariate econometrics tool (cointegration) and a "dynamic" multivariate model (conditional correlation). These two techniques are widely used separately, but they are not often used jointly as part of a research design.

2 Literature Review Related to Market Efficiency

2.1 Introduction

The scope of this chapter is to build an appropriate theoretical framework for the first research objective of this study: to assess the information efficiency of the stock exchanges. This chapter is divided into two parts. The first reviews the concept of the Efficient Market Hypothesis (EMH) and its critics. It begins with Fama's first propositions and ends with the arguments of the behavioural finance school. The second part reviews the methods to test EMH, with a focus on univariate models that capture a series data generating process (DGP). It first investigates the matter of random walk and stationarity. Different unit root tests and their limitations are presented. A robust testing method promoting the joint use of unit root and stationarity test is discussed. The review turns then to an algorithm that uses the criterion of the independent and identically distributed (iid) residuals to ascertain that a model fully captures the DGP of a series. The application of different linear and non-linear models in finance is then discussed. The chapter ends with an outline of the main findings of the discussion.

2.2 Efficient Market Hypothesis

2.2.1 Definitions

The Efficient Market Hypothesis (EMH) is one of the most important but also one of the most criticised paradigms in modern finance. The EMH was first defined formally by Eugene Fama in the late 60s. In his Foundations of Finance (1976), Fama wrote:

> An efficient capital market is a market that is efficient in processing information. The prices of securities observed at any time are based on a "correct" evaluation of all information available at that time. In an efficient market, prices "fully reflect" available information. (p.133)

Fama wrote three articles reviewing work on EMH. Each article has a specific scope. The first one (Fama 1970) establishes the theory. The second one, published twenty years later (Fama 1991), addresses the critics coming from empirical works, mainly findings of evidence of predictability in the market. The third article (Fama 1998) answers critics coming from a radically different school of thought: the behavioural finance school. These articles are used as the main thread for the above discussion.

In his first review of publications on EMH, Fama (1970) presented three forms of market efficiency, each reflecting the quality of information included in security prices:

1. The weak form: security prices reflect all historic market information (past prices, returns trading volume, odd-lot transactions, etc.). The weak form voids the possibility of excess returns through the use of technical analysis, as all historic information is already incorporated in security prices.
2. The semi-strong form: security prices quickly change to new public information (weak-form information, earnings and dividend announcements, common ratios, political and economic information). If the semi-strong form holds, then fundamental analysis cannot provide excess returns, as all public information is already reflected in the asset prices.
3. The strong form: security prices incorporate all public and private information. Private information is therefore useless in a strong form environment.

He argued that empirical evidence is largely supportive of the weak and semi-strong forms of EMH.

However, in the growing literature focusing on testing EMH, different market anomalies contradicting the original understanding of market efficiency are presented. Consequently, other definitions, more pragmatic, were formulated. For Jensen (1978, cited in Timmerman and Granger 2004):

> …a market is efficient with respect to information set Θ if it is impossible to make economic profit by trading on the basis of this information set Θ. (p.17)

This definition, focusing on the importance of economic profit, is shared by many EMH supporters (e.g. Malkiel, 1992).

In his second review of the literature on EMH, Fama (1991) adopted a similar approach to Jensen's and included a sustained economic profit element in his new definition. He also changed the categories of market efficiency: the weak-form tests were now presented as tests for return predictability, the semi-strong tests as event studies, and the strong form tests as tests for private information.

Addressing the event studies, Fama (1991) concluded that on average prices adjusted efficiently to firm-specific information such as investment decisions, dividend changes, changes in capital structure and corporate control transactions. Regarding private information, he depicted a shallower picture and insisted on the importance of the choice of the model, as different models resulted in different findings. But the core of Fama's review focused on return predictability which can be based on past returns or on other variables. He concluded that short-horizon predictability based on past returns, especially first order autocorrelation, does exist but seems minimal and that higher autocorrelation in portfolios may be the spurious result of non-synchronous trading. Furthermore, he questioned the statistical power of the long-horizon predictability surveys. On the other hand, Fama seemed to be interested by cross-sectional return predictability. He argued that size and capitalization are variables that can be used to forecast long-horizon returns.

More recently Malkiel (2003b), in a similar review addressing EMH critics, recognised the evidence of some predictability in empirical studies, what he called the short-term momentum. However, he argued that these anomalies may be statistically but not economically significant, i.e. he did not believe that investors can create portfolios enabling them to earn extraordinary risk adjusted returns. He therefore defined efficient markets as markets that do not allow investors to earn above-average returns without accepting above-average risks. Moreover, Malkiel also noted that as soon as anomalies are public, they fade away.

Timmerman and Granger (2004), in an article on forecasting methods, presented an excellent summary of the important elements of all current definitions of EMH. These elements are: the information set; the ability to exploit the information in a trading strategy; and the economic profit, risk adjusted and net of transaction costs, that the strategy could yield.

The theoretical underpinning of EMH is Muth's (1961) rational expectation concept. According to this argument, the market is comprised of rational investors who independently analyse information regarding securities in order to maximize their utility function. Should a security be mispriced, an opportunity for arbitrage will open. Rational investors will seize this opportunity and act as arbitrageurs, correcting the anomalies of the market. Because new information enters the market randomly, the market is believed to be best described as a random walk.

It is worth noting that the assumptions of the rational expectations models were criticised early in economic literature. For example, Darby (1974) sees two flaws in rational expectations: 1. that each individual has identical expectations and 2. that information is costless. Indeed, he argues that even if the cost of acquiring and digesting data is difficult to quantify, it is not trivial. Moreover, he understands these two problems as interrelated: "if information were really free, everyone would have identical 'rational expectations'" (p. 11). Hence, he concludes that the nontrivial cost of information leads to different expectations and therefore challenges the efficient market theory. For Verrecchia (1982), in a market with costly information, there is an inverse relationship between the cost of information and the 'informativeness' of prices: "as technological improvements permit more information to be obtained at the same cost, trader's increased information acquisition results in prices revealing more information" (1427). However, as price informativeness is only partial, he believes that there is still an incentive to acquire costly information. In a more recent paper, Milani and Rajbhandari (2012) also challenge the rational expectations hypothesis that economic agents have extreme knowledge and capacity to process information. They argue that economic models, especially on the short run, should assume agents have limited knowledge, news about future shocks, adaptive learning, and/or subjective expectations from survey. However for longer horizons, Milani and Rajbhandari (2012) believe that rational expectations models are appropriate.

The most sophisticated critics of EMH are presented by the behavioural finance school, for they not only presented empirical evidence of market inefficiencies, but they also argued against the theoretical assumption of rational expectations and provided an alternative paradigm.

2.2.2 Behavioural finance

Behavioural finance proponents challenged the belief that the market is comprised of rational agents. In a recent survey on behavioural finance, Barberis and Thaler (2002) explained:

> …it (behavioural finance) argues that some financial phenomena can be better understood using models in which agents are not fully rational. More specifically, it analyses what happens when we relax one, or both of the tenets that underline the finance view of rationality. In some behavioural finance models, agents hold beliefs that are not completely correct, most commonly because of failure to apply Bayes' law properly. In other models, agents hold correct beliefs but make choices that are normatively questionable, in that they are incompatible with SEU (Subjective Expected Utility). (p.4)

For them, behavioural finance is based on two building blocks. First, following the work of behaviouralist and economist Kahneman and Tversky (1974, 1979), they believed that investors' psychology is not rational, but can be better described in terms of beliefs such as overconfidence in their own judgement, optimism about their abilities, the use of conservatism and representativeness heuristics, confirmation biases, anchoring, memory biases, etc. Furthermore, investors' preferences seem to be best explained by the prospect theory, whereby agents tend to overweight small probability events, rather than by the traditional expected utility framework.

The second building block is the limit to arbitrage. Behavioural finance sees arbitrage as a risky process and therefore believes in its limited effectiveness (Bareberis and Thaler 2002). The main reason for this stems out of the "noise traders risk": "the risk that the mispricing being exploited by the arbitrageur worsens in the short run" (p.7). This is further accentuated by the fact that many real world arbitrageurs have short, rather than long, horizons (Barberis and Thaler 2002; Shleifer and Vishny 1997). Finally, Barberis and Thaler also insisted on what they call the "model risk": "…even once a mispricing has occurred, arbitrageurs will often still be unsure as to whether it really exists or not" (p.8).

2.2.3 The Rational - Behavioural finance debate

These last two decades, a wide range of articles were published supporting the views of behavioural finance. They focused essentially on identifying and explaining predictability patterns and market anomalies, such as stock prices mean reversion and contrarian investments strategies (for example: DeBondt and Thaler 1985;

Lakonishok et al. 1994), or over or under-reaction to events (for example: Daniel et al. 1998).

Fama (1998) presented a third review of studies challenging the efficiency hypothesis, addressing especially the findings from behavioural finance. He concluded that the long-term return anomalies are chance results, a finding consistent with EMH. He explained:

> …the expected value of abnormal returns is zero, but chance generates apparent anomalies that split randomly between overreaction and underreaction (p.287).

Furthermore, he argued that the anomalies presented by behavioural finance surveys may be related to the choice of methodology. Therefore, with a change in technique (model, sample, return metrics), these long-term returns anomalies tend to disappear.

Methodology is an important point of divergence between the two schools. According to Fama (1991) market efficiency cannot be tested directly, but it needs to be tested with some model of asset-pricing. The problem then is that the choice of model for testing the market will depend on assumptions about this market.

Echoing Fama's "joint hypothesis problem", Barberis and Thaler (2002) wrote:

> In order to claim that the price of a security differs from its properly discounted future cash flows, one needs a model of "proper" discounting. Any test of mispricing is therefore inevitably a joint test of mispricing and of a model of discount rates, making it difficult to provide definitive evidence of inefficiencies. (p.10)

This problem was also pinpointed by Findlay and Williams (2001). In an article reviewing the critical literature on market efficiency, they presented three categories of arguments against EMH: the essence of the efficient market hypothesis, the nature of the empirical work used to test the hypothesis, and the statistical framework of the empirical work. More specifically, they argued that EMH "is not a well-defined and empirically refutable hypothesis" (p.196) and that it assumes integrity of the pricing mechanism and the predominance of rational speculators in the market. Hence testing EMH does not explain pricing mechanisms and is therefore not informative about the market's mechanism. They advocated that the best way to assess the efficiency of a market is to test its relative efficiency against another market. Using an analogy from engineering, they stated:

> Few engineers would ever consider performing a statistical test to determine whether or not a given engine is perfectly efficient - such an engine exists only in the idealised frictionless world of the imagination. But measuring relative efficiency - relative to a frictionless ideal - is commonplace" (p.196-197).

Along the same lines, Timmerman and Granger (2004) believed that an important weakness of the EMH definitions based on an information set is that they do not account for investor's uncertainty about the best model to use. They argued that if the agents do not know the true forecasting model then the practice of using mathematical expectation in the definition becomes less attractive.

However, over time, the two schools of thought appear to converge on certain elements. In a very interesting discussion, Malkiel and Mullainathan (Malkiel et al. 2005) compared their views on the financial world and found some common ground, such as the existence of weak predictability in the market, the existence of noise traders, and the importance of excessive trade volumes. However, they proposed different explanations for these findings. For Mullainathan, predictability is a sign of inefficiency, as arbitrageurs should have entered the game and stripped out the anomalies. On the other hand, Malkiel believed that these examples of weak predictability have no practical application as it is not economically sound for one to enter an arbitrageur position.

Other market characteristics are explained differently by the two researchers. The influence of noise traders is important in behavioural finance. However, Malkiel believed that with as little as 10% of rational traders, all the arbitrage positions are undertaken, a view not shared by Mullainathan. Excessive trading is seen as market inefficiency by behaviouralists as there is no reason to trade excessively if prices are correct. But Malkiel explained excessive trading by money managers' incentives. However, the most important argument supporting EMH put forward by Malkiel is the fact that professionals (i.e. investment funds) do not make excess returns on the long run.

This argument is presented in detail, with empirical evidence, in Malkiel (2003a) which analysed the performance of mutual and equity funds for the period 1970-2001. Malkiel's conclusions were: "the evidence strongly supports passive investment management in all markets – small-capitalisation stocks as well as large capitalisation equities, US markets as well as international markets, and bonds as well as stocks" (p.1).

2.2.4 Regime shift in the EMH paradigm

The debate between proponents of rational and behavioural finance will certainly continue. The two schools of thoughts see and understand the market differently: on one side rational expectation, on the other the human element. However, the findings of behaviouralists pressured the EMH side to develop a more pragmatic approach. They now recognise the existence of market anomalies. Malkiel (Malkiel et al. 2005) even agrees with the overconfidence belief, dear to behaviouralists. The concept of efficiency has shifted from "prices fully reflecting information" (Fama 1970) to economically (in)significant anomalies (Jensen 1978; Malkiel 1992; Fama 1991). Furthermore, behavioural finance has enriched the field of finance research. In the words of Shiller (2006), the behavioural finance revolution "is best described as a return to a more eclectic approach to financial modelling" (p.1). Despite this paradigm shift, EMH remains an extremely helpful conceptual framework to analyse the market.

2.3 Modeling the Data Generating Process

The second part of this chapter looks at methods to test EMH. In order to avoid the joint hypothesis problem, i.e. the choice of asset valuation model, it focuses only on methods based on capturing the data generating process (DGP) of a series. These methods look at the weak form tests (Fama 1970), or test for return predictability (Fama 1991).

2.3.1 Random walk

In the weak form of information efficiency, share prices include all past information. Should new information be available, prices should incorporate it immediately. As new information enters the market randomly, the behaviour of the share prices is therefore believed to follow a random walk. Timmermann and Granger (2004) credited Louis Bachelier, a French mathematician who wrote a thesis entitled "Theorie de la Speculation" in 1900, as being the first to model the behaviour of share prices using the random walk theory. But it is not before the 1960s that this theory was recognized and tested in empirical surveys.

A random walk is a martingale, i.e. a discrete-time stochastic process, such as:

$y_t = y_{t-1} + \varepsilon_t$,

where:

y_t is the price in the current period,

y_{t-1} is the price in the previous period, and

ε_t is the disturbance term in the current period.

Applied to financial time series, the model implies that stock prices are random, that they cannot be predicted. In practice, stock prices are thought to be non-stationary and their data generating process is characterized by a unit root. The random walk hypothesis also requires that the residuals remaining from the linear model be independent and identically distributed (iid) (Fama 1970, 1991).

Many researchers, when testing a series for the random walk hypothesis, believe that the non-stationarity of the stock price series is a sufficient condition to support the EMH weak form. Others argue that a random walk test should also include a close examination of the residuals. If all researchers agree on the importance of the martingale process, they have a different understanding of the utility of the residuals to create potential arbitrage positions.

2.3.2 Stationarity

Most macroeconomic time series appear to be non-stationary in levels, thus current shocks have permanent effects on the levels of the series (Nelson and Plosser 1982). Therefore, regressions using these data are spurious. Hence, testing for the order of integration of the series, i.e. the number of times one needs to difference a series for it to be stationary, is a common practice in macroeconomic and financial empirical research.

The vast majority of the studies in finance conclude that share prices are integrated of order 1, $I(1)$, that is that share prices are non-stationary but share returns are stationary. In that sense, share prices, like many financial time series, behave as most macroeconomic data.

However, some economic variables, such as nominal wages or nominal consumer prices, remain non-stationary after being differenced once (Johansen 1992; Paruolo 1996; etc.). Tahai et al. (2004), using monthly index prices for the period March 1978 to December 1997, showed that the Morgan Stanley Capital International (MSCI) indices for the G7 countries were integrated of the second order, $I(2)$. It is worth noting that in this research the authors used solely the Augmented Dickey-Fuller (ADF) approach to test for the presence of unit root in the series.

2.3.3 Unit root testing

Dickey and Fuller (1979, 1981) first presented tests to detect the presence of a unit root in a series. The test consists of regressing a series on its past values. A trend and/or an intercept can be included in the regression equation. The residuals of the regression are assumed to be identically and independently distributed (iid). The original Dickey-Fuller (DF) test is appropriate to analyse a series that is an autoregressive process of the first order, AR(1). If the series is correlated at higher order lags, then the Augmented Dickey-Fuller (ADF) test is to be used, as it includes further lags of difference values in the regression in order to correct the higher-order correlation. Dickey and Fuller (1979) using Monte Carlo simulation, have computed critical values for the t-ratio as the statistics of the test do not follow the conventional Student's t-distribution. Today, the response surfaces computed by MacKinnon (1996) using a larger set of simulations, are widely used.

Phillips and Perron (PP) (1988) adopted an alternative non-parametric approach to control serial correlation. The Phillips and Perron (PP) test is based on the original DF test, but the t-ratio is modified in order to take into consideration potential serial correlation.

The DF, ADF, and PP tests are called unit root or non-stationary tests as their null hypothesis is that of the presence of a unit root in the series. Thus the null hypothesis is rejected only with extreme values. In an attempt the reverse the "burden of proof", Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) proposed an alternative test which assumes a series to be stationary under the null hypothesis.

These three procedures are very popular for testing series in the financial economics literature.

2.3.4 Limitations of the traditional unit root tests and alternative strategies

Investigating the order of integration of a series is often a more complex procedure than just applying a unit root test. Traditional unit root tests have limitations, which include the low power of the tests, the assumption of linearity of a series and the structural breaks in mean or variance of a series. The following section reviews these problems and presents alternative strategies.

A widely recognised weakness of the traditional unit root tests, such as the ADF and PP tests, is that their power is low if the data generating process is stationary but with a root close to the non-stationary boundary (See for instance: Abidir 1993; Schlitzer 1995; Mahadeva and Robinson 2004; Cook 2004). Furthermore, these tests suffer from size distortions, as the distribution of the test statistics is both non-standard and conditional on the order of the integration of the series, the time series properties of the errors, whether the series is trended or not, etc (Mahadeva and Robinson 2004). Likewise, stationary tests like the KPSS procedure can also suffer from low power and size distortion (Schlitzer 1996).

Schlitzer (1996) argued that the problems of low power and size distortions of the ADF and PP tests are more acute for small sample sizes. For this reason, it is argued that the best way to observe a unit root process is in the long-term behavior of the process (Hamilton 1998). Recognizing the importance of the long-term approach, Sanchez (2003) developed a unit root test based on prediction errors which exploits the relationship between the long-run behavior of a process and the presence of a unit root.

Shin and So (1999) pointed out that the ordinary least-square (OLS) estimator, used in unit root tests such as the Dickey Fuller test, can be very sensitive to outliers. Because many financial time series include outliers, the inference drawn on the basis of the

OLS estimator can be misleading. They proposed an alternative test for autoregressive processes with possibly infinite variance innovations, based on modified M-estimators in which the signs of the regressors rather than the regressors themselves are used as instrumental variables in estimating unit roots.

Mahadeva and Robinson (2004) also underlined the difficulty of differentiating a difference-stationary from a highly autoregressive series or a trend from a difference-stationary series, especially for small samples. They concluded that unit root tests are not definitive information and urged for the statistical tests to be used in conjunction with economic theory.

A strategy which allows controlling the low power and size distortions of the traditional tests is the combined use of unit root and stationary test when analyzing a series for the presence of a unit root (Amano and van Norden 1992; Schiltzer 1996; Brooks 2002). This strategy, called joint hypothesis testing or joint confirmation testing by the authors, allows for robust conclusions.

Schlitzer (1996) tested a set of annual time series of the post-war Italian economy for stationarity, applying the ADF and the KPSS tests. He concluded that while the ADF test strongly supported the unit root hypothesis, the KPSS or the combined procedure (ADF and KPSS) provided less definite conclusions. Furthermore, he stressed the fact that the power of both tests is highly sensitive to the way one parameterizes each test. The strategy reaches a conclusive answer when both tests agree on the nature of the stochastic process.

When applying this joint strategy, Schlitzer (1996) used the conventional critical values of each test. This approach is not shared by others. For example, Charemza and Syzewska (1998) argued that when the DF and KPSS statistics are jointly used, the critical values for those tests should not be taken into consideration. They proposed symmetric critical values via Monte Carlo experiments, which correspond to the probability of type 1 error for the DF test and power of the KPSS test in the case where both cumulative marginal distributions are equal. Therefore, the probabilities of making a wrong decision, that is accepting the null of DF and rejecting the null of KPSS, are identical.

Carrion-i-Silvestre et al. (2001) agreed with Charemza and Syzewska (1998) concerning the need for specific critical values when unit root and stationarity tests are jointly used. However they proposed new critical values for the combined frameworks (DF and KPSS or PP and KPSS) assuming that the joint combined hypothesis of a unit root depends only on the elements that are presumed to be in the deterministic component of the time series, that is, the no-constant, no trend, and with-trend statistics.

However, Keblowski and Welfe (2004) noted that the values computed by Charemza and Syczewska (1998) and Carrion-i-Sylvestre et al. (2001) are mainly for large samples while in the empirical work samples are usually limited. Thus, they computed values via Monte Carlo experiments for the joint ADF-KPSS test for small samples (n= 20 to 45). Furthermore, they explored the power of the joint test.

Another limitation of the unit root test is related to the assumption of linearity of a series. Narayan (2005) proposed an alternative procedure to test for the random walk hypothesis, using a threshold autoregressive (TAR) model. He first examined the linearity of the data generating process of the Australian stock price index (ASX all ordinaries) and New Zealand's stock price index (NZSE capital index). As the processes appeared to be non-linear, he tested for the presence of a unit root using the Carner and Hansen (2001) tests and found that both ASX and NZSE indexes were non-stationary at levels. He concluded that the Australian and New Zeeland stock markets are efficient. Along the same lines, Menezes et al. (2004), who wanted to take into consideration the asymmetric adjustment of the Portuguese stock market over the business cycle in their model, applied a threshold autoregressive model (TAR) and a momentum threshold autoregressive model (M-TAR) to address the problem of asymmetry as well as the low power of the unit root test in the presence of asymmetry. They mainly observed that the Johansen method did not find cointegrating vectors when the M-TAR model indicated asymmetry (the Johansen cointegration method is essentially a test for a unit root).

A further limitation stems from the fact that economic time series often exhibit structural breaks (Cook, 2004). The presence of structural breaks in the deterministic trend component can reduce the power of unit root tests (Perron 1989; Leybourne et al. 1998). Likewise, standard unit root tests have low power when the series is subject to a stochastic trend break (Balke and Fomby 1991). On the other hand, Cook (2004) mentioned that the original DF test can have high power when a break in mean occurs at the start of the sample period. He also stressed the fact that the DF test can suffer from severe size distortion when applied to unit root series subject to a structural break.

These structural breaks also make it difficult to ascertain whether the true DGP is stationary or not. Contradicting the Nelson and Plosser (1982) unit root hypothesis for macroeconomic data, Perron (1989) argued that macroeconomic series, including stock prices, are more likely to be stationary when the trend function is allowed to exhibit occasional change. In a recent study, Perron and Rodriguez (2003), using the GLS detrending unit root test and considering two models, a change in the slope and a change both for the slope and the intercept, tested a sample of common stock prices for the period 1871-1970. They found some evidence, though non-unanimous, against the null hypothesis of a unit root.

Taking the opposite view, Hsieh (1991) believes that in the long run stock returns are not stationary:

> Over a long time period, it is difficult to make a case that the behavior of stock returns remains unchanged. Changes in economic fundamentals, e.g., wars, can shift the mean return (represented by '2-mean' model). Change in the operating procedure of the Federal Reserve, e.g., switching from an interest rate to a money supply target during 1979-1982, can shift the volatility of financial markets (represented by the '2-variance' model). (p. 1856-1857)

The stock prices series may therefore include structural breaks. Cavaliere (2003) investigated the effects of Markov regime switches on the asymptotic behavior of unit root and stationarity tests. He focused on switches in linear trend components, in the mean of transitory components, and in the variance of both permanent and transitory components. He concluded that unit root and stationarity tests (such as KPSS) are not reliable in the presence of structural breaks in linear trends. He therefore suggested that a statistical model allowing for Markov-switching trends should be used in order to reduce the spurious acceptance of the unit root hypothesis.

Using a Monte Carlo experiment instead of asymptotic theory, Cook (2004) examined the finite-sample properties of modified unit root tests based upon weighted symmetric estimation and recursive mean adjustment in the presence of structural breaks. He found out that these modified tests have high power in the absence of structural change. However, when applied to a series with a single break in mean, the size of the tests may be robust but at the expense of an important loss of power.

Similarly Carrion-i-Silvestre (2003) investigated the effect of misspecification error in the determination of a level shift for the KPSS test applying Monte Carlo simulation. He concluded that the rate of divergence of the KPSS test is higher than that of the associated error due to failure to allow for structural break, stressing therefore the importance of the correct specification of the breaking date for the KPSS test.

It is clear from the literature that testing for stationarity can be a complex procedure and that the problems of the power of the tests, linearity and structural break in the series need to be taken into consideration.

2.3.5 Nonlinearity

A model captures all the information included in a series if its residuals are independently and identically distributed (iid), i.e. the residuals do not include any further information. This criterion is one of the assumptions of a well-specified model. In the literature, however, the iid of the residuals is often assumed but not tested, especially when assessing the order of integration of a series is a prelude to further investigation (for example cointegration) or the use of a vector auto-regressive (VAR) model. But, if the linear trend of a series is modelled and the residuals do not comply with the iid assumption, this indicates the presence of nonlinear dependencies in the series. The consequences of the nonlinearity in stock market returns are twofold.

First, at least theoretically, the residuals may include important information for predicting future share prices, which would be in breach of the weak-form EMH. However, Hsieh (1991) argued that nonlinearity does not necessarily contradict market efficiency: ‘the fact that returns themselves are not iid (and therefore potentially predictable) says nothing about the predictability of forecast errors' (p.1856; see also Sewel et al. 1996).

Second, nonlinear dependencies raise questions about asset pricing models, such as the Capital Asset Pricing Model (CAPM), which are usually linear in nature (Sewel et al. 1996).

It is therefore important to identify the nature of nonlinearity of a series. In finance, two types of nonlinearity are considered: nonlinear stochastic processes and nonlinear deterministic or chaotic processes.

Hsieh (1991), Sewel et al. (1996) and Al-Loughani and Chappel (1997) used a similar multi-step strategy to model the data generating process of a series. This strategy is based on the formal testing of the iid residuals as decision criterion. In their paper, they used the Brock, Dechert and Scheinkman (BDS) test (Brock et al., 1987), a procedure that tests for the serial correlation of a series, to ascertain whether the residuals of a model are iid. As noted by Hsieh (1991), the 'BDS has good power to detect at least four types of non-iid behaviour: 'linear dependence, nonstationarity, chaos, and nonlinear stochastic processes' (p.1856).

The first step of the strategy is to estimate an auto-regressive moving average (ARMA) process to capture all the linear dependence of a series. The BDS test is then used to test the residual of the model for serial correlation. If the null hypothesis of iid is accepted, then the model is believed to appropriately represent the data generating process of the series. If however the null is rejected, then a stochastic nonlinear process, the general auto-regressive conditional heteroskedastic (GARCH) model is estimated to capture the nonlinear dependences in the series. The BDS test is again applied on the residuals of the new estimates. In the case of non-rejection of the null, the data generating process is identified with the joint modeling of the linear dependencies (ARMA process) and the conditional variance (GARCH process).
If the null hypothesis is rejected again, then this might indicate that the data generating process of the series is not stochastic but deterministic in nature. The strategy continues then with the estimation of chaotic processes, until the null of the BDS test is not rejected and an appropriate model chosen.

The problem with nonlinearity in the data generating process is the diversity of nonlinear stochastic or deterministic models. In finance, the nature of the nonlinearity in data is often thought to be stochastic in nature and caused by a heteroskedastic variance, i.e. a non-stable conditional variance. This type of nonlinearity can be captured with a GARCH model, which estimates the variance of a series as conditional on its previous realisations. First developed by Engle (1982), the auto-regressive conditional heteroskedastic (ARCH) model was generalised by Bollerslev (1986) into the GARCH model. Heteroskedastic variance models can effectively represent volatility clustering, a stylised fact in finance. When combined, an ARMA-GARCH model jointly estimates the first and second moments of a series.

Modelling and forecasting volatility is extremely important in finance, especially as volatility is an essential component of options valuations. Hence, the finance literature is comprised of numerous examples of applications of ARMA-GARCH models. The next section reviews some characteristic methods and presents evidence of stochastic nonlinearity in stock returns.

2.3.6 Stochastic nonlinearity: volatility clustering

Triggered by the fact that the frequency of large moves in stock markets is greater than would be expected under a normal distribution, Hsieh (1991) explored the nature of stock returns and more specifically whether the nonlinearity exhibited by these returns is stochastic or dynamic. After an overview of different types of chaotic processes that might be relevant in financial economics, Hsieh looked first at the power of the BDS test, the diagnostic procedure he intended to use to choose a model. Using Monte Carlo simulations of 2000 replications of 1000 observations, he tested 11 non-iid processes: first order auto-regression (AR1), first order moving average (MA1), a '2-mean'model, a '2-variance' model, a nonlinear moving average (NMA), the threshold autoregression (TAR), an autoregressive conditional heteroskedasticity (ARCH) model, a generalised autoregressive conditional heteroskedascity (GARCH) model, an exponential generalised autoregressive conditional heteroskdascity (EGARCH) model, a Mackey–Glass and a Sine model; the latter two being chaotic processes. The results showed that the BDS test easily detects nonlinearity in all processes but EGARCH. He then looked at the size of the test for residuals instead of raw data, asking the following question: 'will linear filtering change either the asymptotic or the finite sample distribution of the test statistics?' (p.1854). Using the same Monte Carlo procedure, he examined the residuals generated by five processes: AR(1), MA(1), NMA, GARCH and EGARCH. He discovered that asymptotic distributions approximate well the finite sample distribution when using the residuals of the three first processes; however it rejected too infrequently in the case of standardized residuals from GARCH and EGARCH models. He concluded therefore that overall the BDS procedure is an appropriate diagnostic test.

After investigating the size and power of the BDS test, Hsieh (1991) turned to stock returns. The sample is comprised of weekly returns for value-weighted index and the equally weighted index from the Center for Research in Securities Prices (CRSP) for the period 1963 to 1987. Filtering them with an autoregressive process whose lag lengths were determined by the Schwarz information criterion, he found strong evidences of nonlinearity in the series. Continuing, he applied different models to the residuals. He found that there was no evidence in favour of low complexity chaotic behaviour and that traditional ARCH-type models (ARCH, GARCH, EGARCH) did not fully capture the nonlinearity. He finally chose a specifically built conditional heteroskedasticity flexible model. Hsieh's conclusions emphasised the importance of nonlinearity in the conditional density functions of stock returns. Moreover, he argued that the nature of nonlinearity was to be found in conditional heteroskedasticity rather than in conditional mean changes (chaotic dynamic).

Sewel et al. (1996) used a similar algorithm to analyse the weekly returns of six major stock indices (the US, Korea, Taiwan, Japan, Singapore, and Hong Kong) and the world index for the period 1980 to 1994. They first filtered the returns using an autoregressive moving average (ARMA) model to remove all linear dependencies and applied the BDS test on the residuals. As they were not iid, they used a GARCH (1,1) model to remove the conditional heteroskedasticity from the residuals of the ARMA process. The result from the BDS test indicated that the nonlinearity in the Japanese and Korean indices was stochastic and captured with an ARMA-GARCH model. However, the BDS test showed mixed evidence for the S&P 500, Hong Kong, Taiwan and Singapore indices, leaving the possibility that these series were generated by chaotic processes. Hence, they used a K-map to identify potential nonlinear deterministic behaviour. The nature and the results of this research are described in section 2.3.8 which focuses on chaotic models. This strategy was also applied to UK indices by Al-Loughani and Chapell (1997) and Opong et al. (1999).

Al-Loughani and Chappell (1997) focused on the daily returns of the FTSE 30 for the period June 1983 to November 1989. They tested the index returns for stationarity using the DF and ADF procedures but found that the residuals were not iid as the BDS null hypothesis was rejected at 5% level, suggesting that there was some further unexplained structure in the data. A GARCH-M (1,1) model was finally chosen as it satisfied the iid decision criterion.

In the same spirit, Opong et al. (1999) also examined the behaviour of UK indices. Their sample was the daily prices of the FTSE All Share, FTSE 100, FTSE 250, and FTSE 350. They also found that a GARCH (1,1) process captured all the nonlinearity in the series, a conclusion in line with Al-Laghouni and Chappel (1997) and Sewel et al. (1996). However, their article included two interesting results. First, they applied two diagnostic tests, the Hurst modified Rescaled Range procedure (R/S) and the BDS test, and they found that the R/S analysis was not powerful enough to detect non-iid residuals. Second, they believed that 'structural change in the mean or the variance of an otherwise iid series could lead to rejection of iid by the BDS test (p.279; see also Hsieh 1991). To overcome this problem, they suggested dividing the series into two periods and conducting the analysis again.

The data generating process of other stock markets have also been researched using this strategy. For example Panagiotidis (2005) attempted to test the efficiency of the Greek stock exchange after the introduction of EMU, as well as the effect of market capitalization on market efficiency. An interesting element of his research is that he used five different tests for assessing the distribution of the residuals: the BDS, the McLeod-Li, the Engle LM, the Tsay, and the Bicovariance tests. Like the papers described above, he choose a GARCH (1,1) process to parsimoniously model the data generating process of the daily prices of the "high capitalization" FTSE-ASE20, the "medium size companies" FTSE-Mid40 and the "small capitalization" FTSE-Small Cap for the period June 2000 to March 2003. Because of the presence of volatility clustering in the three series after the introduction of the common currency, he concluded that the EMU did not increase the efficiency of the Greek stock market.

This result is in line with results of similar studies for the Greek market (Apergis and Elptheriou 2001; Siourounis 2002). He also found that past volatility is important for the FTSE20 and FTSE Mid40 series, but not for the Small cap series, indicating that the lower capitalization component of the market tends to be more efficient.

Lim and Brooks (2009) also used five diagnostic tests, the McLeod-Li, the Engle LM, the BDS, the Hinich bispectrum and the Tsay tests, to analyse the DGP of the Shanghai and Shenzhen stock exchanges. They found strong evidence of nonlinear serial dependence in the returns, but did not attempt to model further the series. They concluded that the Chinese markets were not weakly efficient. They argued that the behaviour of the Chinese investors, who trade like noise traders, explains the findings.

The strategy presented above and based on the iid criterion is simple and effective to identify the data generating process of a series. Different diagnostic tests can be used, but the BDS test is widely recognized as appropriate. From the articles reviewed, there is strong evidence of nonlinearity in stock market index returns as linear models fail to fully identify their data generating processes. In all the cases, this nonlinearity was stochastic in nature and simple low order GARCH models seemed appropriate to capture it. This nonlinearity is caused by the volatility clustering of the index returns, a stylized fact recognized in finance literature. This volatility clustering is often interpreted as an anomaly and therefore understood as a sign of inefficiency.

However, the nature of nonlinearity can be caused by other factors, such as long memory process or chaos. The next two sections are dedicated to these processes.

2.3.7 Stochastic nonlinearity: long memory

For a series exhibiting a unit root at price levels, the rejection of the iid residuals hypothesis in the returns can be caused by a long memory pattern. Such a phenomenon is characterized by autocorrelation which implies some level of predictability and therefore invalidates the weak form of EMH.

This section is divided into two parts. The econometric techniques testing for the presence of long memory are first presented briefly, followed by a discussion of the results of long memory studies.

Testing for long memory:

A long memory process can be modeled using fractional integration. Close to an ARIMA process, an autoregressive fractionally integrated moving average model, ARFIMA (*p, d, q*), allows for the level of integration be defined by any real non-integer number:

$\phi(L)(1-L)^d X_t = \theta(L)\varepsilon_t,$

where: $\varepsilon_t \sim iid(0, \sigma^2),$ and $(1-L)^d$ is the fractional differencing operator.

A time series X_t is said to be fractionally integrated of order (*d*), if *d* is a non-integer (Granger and Joyeux 1980, cited in Sowell 1992). A time series is covariance stationary if *d* takes values between -0.5 and 0.5. If *d* is greater than zero but smaller or than 0.5, then a series is said to have a long memory or to be persistent. For equity, it means that stock or index returns would return to their long-term trends in the future. If *d* equals zero, the series is said to have no memory. Stock or index returns would never return to the long-term trend, except by pure chance. Finally, if *d* lies between 0 and -0.5, the series is said to be anti-persistent (Assaf 2006).

Equity returns exhibiting long memory behaviour have therefore an important implication for traders as they may include some level of predictability. Common procedures to detect the presence of a long memory process are the Hurst-Mandelbrot rescaled range analysis (R/S) (Hurst 1951; Mandelbrot 1972) and the Lo modified rescaled range test (MRR) (Lo 1991). Procedures to estimate the order of fractional integration, *d*, are the Geweke-Porter-Hudak test (GPH) (Geweke and Porter-Hudak 1983) and the Robinson tests (Robinson 1994). Baillie (1996) presents an extensive discussion of the different tests of fractional integration and their properties.

It is worth noting that in certain cases, the interpretation of outliers can be important when testing for long memory. Tolvi (2003) demonstrated that in some cases, mainly for the smaller stock markets, outliers biased the estimated fractional integration parameter to zero.

Evidence of long memory:

Different stock market indices have been tested for long memory, with contradicting results. Outcomes of long memory studies are presented in the following pages, first looking at evidence of long memory in returns series, then in returns volatility.

Cajueiro and Tabak (2004) analyzed daily returns of 6 indices from the Asian market (China, Hong Kong, Singapore, and Shanghai and Shenzhen class A and B shares) for the period October 1992 to December 2000. They used the classical Hurst R/S approach but also provided a dynamic analysis of the Hurst exponent, using a rolling sample, to account for the time evolvement of the market efficiency. They concluded that the three markets presented evidence of a long memory process and suggested that market capitalization and liquidity may explain the difference in the intensity of these processes. On the other hand, Cheung and Lai (1995) used the MRR and the GPH analysis to investigate long memory patterns in 18 national indices for the period 1970 to 1992. Their sample was comprised of the monthly returns and excess returns of these indices. The results of the MRR procedure provided no evidence of long memory in the return series. However, the results of the GPH analysis indicated long memory in four of the 18 indices. They concluded that "the results on the whole are not supportive of the presence of long memory in stock returns." (p.612)

On the other hand, Blasco and Santamaria (1996) did not find strong evidence of long memory for the Spanish stock market. Testing first the daily returns for the period January 1980 to December 1993 of the Madrid Stock Exchange General Index and different sectoral indices with the BDS and the Hurst Mandelbrot R/S analysis, they concluded that the series were not iid. They then applied the modified rescaled range (MRR) and the GPH tests on the Spanish indices. The results indicated the possible presence of short term predictability but seemed sensitive to the choice of the tests' parameters. However, the authors concluded that the Spanish market is not weakly efficient as the iid assumption is not corroborated by their analysis. It is worth noting that the authors applied the BDS analysis without filtering first for linear dependence.

Using a more recent procedure for fractional integration, the Robinson tests (1994), Caporale and Gil-Alana (2004a) analysed the daily prices of the S&P 500 index for the period 1928 to 1991. Dividing the overall sample of 17,000 observations into 10 subsamples, they found that ‘the degree of dependence remains relatively constant over time, with the order of integration of stock returns fluctuating slightly around zero’(p. 382). Arguing the size of the sample, they concluded that ‘a standard model in first differences rather than a fractionally integrated one might be appropriate for stock returns’. (p. 382). In an article published two years earlier (Caporale and Gil-Alana 2002), the authors had used the S&P 500 as well, however with annual frequency and for a large time span, 1890-1993. Applying the Robinson (1994) spectral analysis, they had already concluded that the returns were $I(0)$.

Tolvi (2003) showed that in certain cases, the interpretation of outliers can be important when testing for long memory. Using a sample of monthly stock price indices for 16 OECD countries, he demonstrated that in some cases, mainly for the smaller stock markets, outliers biased the estimated fractional integration parameter to zero.

Long memory patterns can be found in the first and second moments. Assaf (2006) looked for long memory behaviour in returns and in volatility. He studied stock markets of the Middle East and North Africa (NEMA) region: Egypt, Morocco, Jordan and Turkey. Using daily returns for the period 1997 to 2002, he first applied the MRR (Lo, 1991) and the rescaled variance test (Giraitis et al. 2003, cited in Assaf 2006). Then, using the Sowell (1992) procedure, he estimated the degree of fractional integration. The results were that Egypt and Morocco presented long memory evidence in returns, Jordan and Turkey exhibited antipersistence, and all four markets displayed strong persistence in their volatility. Assaf showed that an ARFIMA process provided a superior forecasting model for Egypt and Morocco, but that ARIMA process was sufficient for Jordan and Turkey. The author concluded that evidence of a long memory was strong in the MENA region, with evident consequences for equity derivatives trading.

Lobato and Savin (1998) also tested for the presence of long memory process in stock market returns and volatility. Using the daily returns for the S&P500 index for the period 1932 to 1994, they apply the semi-parametric method of Lobato and Robinson (1998). They found no evidence of long memory in returns, but evidence in the squared returns, i.e. in volatility. They argued that theory suggests that long memory in stock volatility can be spurious and caused by nonstationarity of stock returns or, in the case of stock index, based on aggregation. In order to strengthen their results, they tested for long memory the returns and squared returns of the 30 individual stocks comprising the Dow Jones Industrial Average for the period 1973-1994. Again, they found no evidence of long memory in the individual stock returns and mixed evidence for the squared returns. They concluded therefore that their results pointing long memory in volatility are not spurious.

Similarly, Po (2000) tested the daily returns of the S&P 500 index, Dow Jones Industrial Average index and its 30 constituent stocks for volatility long-term memory for the period July 1962 to June 1995. He used the MRR and GPH tests and three proxies for volatility: the absolute mean deviation, the squared deviation and the logarithm of the absolute deviation. He concluded that these indices and stocks present strong evidence of long memory in their volatility.

On the other hand, Vougas (2004), when modelling volatility using a GARCH model, showed that evidence of long memory, otherwise present in returns, disappeared. Specifically, he first found strong evidence of long memory in the daily returns of the Athens main index (ASE) for the period 1990 to 2000, applying an ARFIMA process and using the AIC information criterion. However, he found weaker evidence when investigating with the SBC information criterion. He then decided to model volatility and estimated a GARCH-ARFIMA process, following the procedure of Baillie et al. (1996). He concluded that, for the data under consideration, 'long memory evidence is weaker (if not absent) when volatility of returns is modelled properly' (p. 459).

There is therefore mixed evidence for long memory patterns in the mean or the variance of a series. But fractional integration is still a stochastic process. Nonlinearity can be generated by a deterministic process, such as chaos.

2.3.8 Deterministic nonlinearity: chaos

There are theoretical arguments to consider chaotic processes in finance, mainly related to the assumption regarding the non-rational nature of the economic world and its agents. Moreover, stylized facts of financial time series, such as volatility

clustering, may be generated by a chaotic process. In any case, evidence of chaos in financial markets would invalidate EMH.
Hsieh (1991) put forward two main reasons for the interest in chaos in financial economics. First, with the Box-Jenkins models, i.e. in the 'stochastic world', the economy has a stable equilibrium, but is constantly perturbed by external shocks, which create the dynamic behaviour of the economy. On the other hand, 'in the chaotic growth models, the economy follows nonlinear dynamics, which are self-generating and never die down. The fact that economic fluctuations can be internally generated has a certain intuitive appeal' (p. 1840).

The second reason is related to the incapacity of linear models to represent the observed sudden burst of volatility and occasional large movements in stock returns. Chaotic dynamics, which are nonlinear by nature, can therefore be more appropriate to represent the data generating process of stock returns (Hsieh 1991).

Kyrtsou and Terazza (2002) argued that the chaotic behaviour of stock markets is related to complex systems which are the consequence of markets being comprised of heterogeneous agents: 'a system is said to be complex when it exhibits some types of order as a result of the interactions of many heterogeneous actors' (p. 408). In their view, the rational expectations hypothesis in economics, where all agents are assumed rational, hence homogeneous, does not hold:

> …traders differ in many aspects. For example, they face transactions costs, have different information sets, use different equilibrium models, work with different time scale and time horizons, and have different opinions or expectations about tomorrow's dividends and stock prices. (p.412).

There are different models explaining how interaction between heterogeneous agents produces complex dynamics.

> In these nonlinear models, complex asset-price fluctuations are triggered by an interaction between a stabilizing force driving prices back towards their fundamental value when the market is dominated by fundamentalists and a destabilizing force driving prices away from their fundamental value when market is dominated by speculative noise traders. (Kyrtsou and Terazza 2002, p.408)

However, it may be difficult to differentiate between nonlinear stochastic and deterministic processes. Kyrstou and Terraza (2002) explained that a noisy chaotic process, which is believed to capture the behaviour of stock returns, presents similarities with an ARCH process, in terms of high kurtosis, nonlinear structure, fractional integration coefficient equal to zero and high correlation dimension. Using the CAC40 daily returns series for the period 1987 to 1999, they applied different procedures, including the GPH fractional integration test and the Lyapunov Exponent (LE) to test for chaotic behaviour. They concluded that 'complex systems, such as stock markets, cannot be described by a purely deterministic system…'and that 'the Paris Stock Exchange can be modeled as a nonlinear system buffeted with noise (noisy chaos)' (p.426).

To identify chaotic behaviour is therefore not straightforward. Hsieh (1991) believes that the interest in chaos in finance should focus on low complexity chaotic behavior, as highly chaotic behaviour cannot be detected using a finite amount of data. Moreover, only a not-too-complex chaotic process allows for short-term complexity. Hommes and Manzan (2006) identified two main procedures to test time series for chaos: to 'estimate the correlation dimension measuring the fractal nature of a possibly underlying strange attractor'…or… to 'estimate the largest Lyapunov exponent (LE) which, when found to be positive, measures the sensitive dependence on initial conditions so characteristic of a chaotic system.'(169-170). However, the authors noted that these procedures are highly sensitive to noise. Hommes and Manzan (2006) echoed here an issue raised by Kyrtsou and Serletis (2006): the interpretation of outliers. Are the outliers exogenous phenomena which therefore should be neglected in empirical work or are they endogenous to the system and should be kept as they are informative about the generating mechanism? For example, Kyrtsou and Serletis (2006) tested daily Canadian exchange rates for a period of 30 years. When outliers were kept in the sample, there was evidence of noisy chaotic structures; however if the outliers were removed, the best performing model was a GARCH (1,1).

The BDS analysis does not test directly for nonlinearity or chaos. The null hypothesis of the test is that the values of the variable are iid. However, it can be used as indirect evidence about nonlinear dependence, whether chaotic or stochastic (Kyrtsou and Serletis 2006). It is therefore a first step in searching for chaotic behaviour in a series. However, Kramer and Runde (1997) showed that rounding in prices may result in rejection of a correct null hypothesis of iid returns. They therefore concluded that evidence in favour of chaos in stock returns may be caused by the fact that prices change only in discrete ticks.

With reference to the potential weaknesses of the BDS analysis, related to the choice of the parameters and the sensitivity to noise, McKenzie (2001) decided to look for chaotic behaviour in major stock market indices applying both the BDS and the close return tests, a procedure that searches for unstable periodic orbits embedded in the strange attractor. The results of the two analyses were sometimes conflicting, but the author did not find evidence of chaos: ‘the results furnished strong evidence of nonlinearity although it (the data) was not found to exhibit sensitive dependence on initial conditions, and was not chaotic’ (p. 51). McKenzie concluded that the close return test gives stronger evidence of nonlinearity in the data than the BDS procedure.

In section 2.3.6, it was noted that the multistep strategy first developed by Hsieh (1991) also included deterministic nonlinearity as one class of models. Indeed Hsieh (1991) and Sewel et al. (1996) investigated the hypothesis that stock returns are generated by chaos. Hsieh concluded that nonlinearity is best captured by stochastic processes. On the other hand, the results of Sewel et al. presented mixed evidence. They used a procedure inspired by Larrain (1991): the K-map and Z-map. The K-map captures the nonlinear dynamics and the Z-map represents the behavioural elements. In this analysis, they estimate an equation comprised of the K-map, which expresses a series as a nonlinear function of its lag values and the Z-map, which is a proxy for market integration, as represented by the Morgan Stanley World Index. If the K-map overpowers the Z-map, then there is evidence of erratic behaviour. Sewel et al. used data from six major stock indices. Two of these proved to be generated by a stochastic process whereas the remaining showed mixed results (see section 2.3.6). The findings of the K and Z-map showed that ‘those stock markets not found to be stochastic are integrated with the World Market to varying degrees’ (p. 99). Moreover, ‘nonlinearity could arise from a representation of the time series as a nonlinear function of prior observations.’(p.101). This finding might be consistent with chaos but does not prove its existence.

2.4 Summary

2.4.1 Efficient market hypothesis

The Efficient Market Hypothesis is an important theory in modern finance. Based on the economic concept of rational expectations, it classifies markets according to their level of information efficiency.

The critics of EMH and the rational school can be organised in three categories: critics of the rational expectation assumption, the theoretical foundation of EMH; critics of the methods used to test EMH in finance; and empirical evidence supporting the existence of market anomalies.

The Behavioural Finance school questioned the notion of rationality in financial markets. For them, markets are driven by the psychology of the investors which they describe as non-rational. Their research put forward evidence of this lack of rationality in markets. The rational school acknowledges some of the behavioural school's findings but still believes that on an aggregate level the rational investors' actions are sufficient to render markets efficient.

Testing EMH involves a methodological issue: the joint hypothesis problem. Indeed, testing EMH using an asset valuation model implies testing the model itself. The joint hypothesis problem remains an important hurdle, recognized by the rationalists.

Finally, the finance literature includes a lot of evidence of market anomalies. These findings challenge directly the weaker form of EMH. The position of the rational school is that this evidence of predictability is based on short term momentum, which fades away once public, and that much of it is statistically but not economically significant.

Following these critics, the EMH has undergone a paradigm shift. The understanding of efficiency tends to be more flexible and the new definition addresses some of the criticisms. For example, the description of information efficiency moved from a strict 'full reflection of information' to the concept of 'abnormal economic profit'.

2.4.2 Data generating process

One way to circumvent the joint hypothesis problem is to analyze directly a financial series and to identify its data generating process, rather than using a method based on asset-valuation models.

According to the weak form of EMH, the price of a share is expected to follow a random walk process. This type of DGP translates the concept that in an efficient market, the price of a share cannot be predicted using past information.

A financial series that follows a random walk process is usually integrated of order one, i.e. it is nonstationary in levels and stationary after being differentiated. Therefore, an important first step is to test a series for stationarity. There are many unit root tests and each of them has limitations. Overall, the problems related to the unit root tests are usually their low power, the assumption of linearity of the series tested, the presence of outliers and structural breaks in the series. Each testing procedure addresses a specific problem, but none of the tests is superior to the others. A robust strategy involves the joint use of unit root tests (e.g. ADF) and stationarity tests (e.g. KPSS) as it addresses the problem of low power of the tests.

However, the DGP of a financial series is often more complex than a simple random walk process. An interesting algorithm uses the iid residuals as a decision criterion to choose the best model to capture the DGP of a series. It first looks at linear models from the ARMA class. If the iid residuals criterion is rejected by the diagnostic tests, then it investigates nonlinear models. The strategy stops once a model satisfies the decision criterion.

The general outcome from this strategy is that most of the financial series includes some elements of nonlinearity. This nonlinearity can be modelled using stochastic or deterministic behaviour.

A natural first direction for finance investigation is the stochastic road where nonlinearity can have two causes: long memory and volatility clustering. Models to capture long memory are from the fractional integrated autoregressive moving average (ARFIMA) class, and for volatility clustering, models from the general autoregressive conditional heteroskedastic (GARCH) class. Findings show strong evidence supporting GARCH models to capture DGP and weaker evidence in favour of long memory processes. Structural breaks and outliers can again be an issue when using these models. A solution is to divide the initial sample into subsamples around the expected break date.

Deterministic nonlinear processes are also considered in finance. However, there are two main problems related to this approach. The first issue is to identify the appropriate model as there numerous types of nonlinear deterministic processes. The second issue is the difficulty of differentiating in practice between some chaotic and stochastic nonlinear models.

Overall, empirical evidence shows that the data generating process of financial time series are best captured with ARMA-GARCH, modelling both the mean and the conditional variance. The volatility clustering is interpreted by many as a breach of the weak form of EMH. Others argue that no abnormal return can be yielded from strategies based on these anomalies and therefore conclude that the weak form of EMH is still valid.

2.5 Implications of the Literature Review on the First Research Objective

The scope of the first research objective is to assess the impact of Euronext integration on the efficiency of the Dutch, Belgian and French stock markets. The EMH paradigm has been evaluated these last decades, but it remains an important paradigm in finance research and is used as the theoretical framework for the first research question.

The two main research schools in finance, the Rational and the Behavioural schools, have different approaches to research which stems from their different understanding of the market. Behaviouralists, who believe in the lack of rationality of the market, tend to research the market and its participants qualitatively. The rationalists, who have adopted the rational expectation paradigm, focus more on quantitative research involving financial and macro-economic time series. The rationalist approach is adopted for the first research objective and second objective of this thesis.

Consequently, the empirical work presented is quantitative and the methodology is inspired from the review of the literature.

There are two main approaches to test the EMH of a market. One way is to use an asset-valuation model, but then the joint-hypothesis problem occurs. The other way is to adopt a model-free approach which concentrates on the identification of the DGP. This popular approach applies an algorithm based on model fitting and the use of a set of diagnostic tests. The methodology for the empirical work for the first research objective is based on this algorithm.

3 Literature Review Related to Market Integration

3.1 Introduction

This chapter reviews the literature relating to the second research objective: to assess the market integration between the three stock exchanges following the Euronext incorporation. It is divided into three sections. Market integration is not a complete theory, rather a set of propositions and concepts. Hence the chapter opens with a discussion of different definitions of market integration from the finance literature. The next section investigates the consequences of market integration and its potential impact on international portfolio diversification. The last section reviews the different methods used to assess the level of integration. The econometric methods presented are classified into two categories: static models where one model is estimated over a period, such as cointegration, and dynamic models where processes capture changes in all observations, such as conditional correlations. The chapter ends with a summary of the main findings section.

3.2 Definitions

A common definition of stock markets integration is that integration is a function of the degree of co-movement in asset prices (Bekaert and Harvey 1995; see also Tahai et al. 2004; Choudhry et al. 2007). A broader definition includes non-synchronous movements between markets: 'if two markets demonstrate greater co-movement on the same day, or a stronger lead/lag relationship across days, we interpret this to represent greater integration between the two stock markets' (Bracker et al. 1999, p.2).

There are also more complex definitions. For example, Baele et al. (2004):

> The market for a given set of financial instruments and/or services is fully integrated if all potential market participants with the same relevant characteristics:
> 1. face a single set of rules when they decide to deal with those financial instruments and /or services;
> 2. have equal access to the above-mentioned set of financial instruments and/or services; and
> 3. are treated equally when they are active in the market. (p.6)

The authors stressed that their definition has three important components: 1. financial integration is independent of the financial structures within regions; 2. frictions can subsist in integrated markets as long as frictions affect the markets symmetrically; and

3. full financial integration entails that market participants and firms listed have the same access to financial intermediaries and clearing platforms.
This latter definition is interesting because it describes financial integration as a complex phenomenon. However, because of its complexity, it is difficult to relate it to a clear testing framework. Hence, this study adopts the definition of financial integration as an increase in markets co-movements as a theoretical framework.

An important discussion in the literature is whether stock market integration is an isolated trend or part of a wider reality. In an introductory article of a special issue of the International Review of Financial Analysis on international equity market integration, Kearney and Lucey (2004, p. 572) placed stock market integration in the general context of capital market integration, itself a part of economic integration.

Bekeart and Harvey (1995) believed that the degree of integration, or segmentation, of a market with world capital markets is greatly influenced by the economic and financial policies followed by its government or other regulatory institutions. In other words, the degree of economic integration affects the degree of capital integration (Tahai et al. 2004, p. 327).

The factors influencing market integration were also debated. Masih and Masih (2004) believed that legal and economic common frameworks play an important role. They argued that European Union membership, EU institutional agreements concerning equity markets, the growth of Euro-equity markets, the common monetary policies, as well as other global trends, all explain European stock market integration (p. 21).

Fratzcher (2001), Adjaoute and Danthine (2003), Baele et al. (2004) and Hardouvelis et al. (2006) focused their research on financial integration in the Euro area. Fratzcher and Hardouvelis et al. argued that financial integration in the Euro-zone began in the mid-1990s but that the European Monetary Union (EMU) has increased the phenomenon. For Fratzcher, "a high degree of financial integration in Europe may at least in part be explained through the convergence of monetary policies among European and in particular Euro area countries" (p. 27). Hardouvelis et al. put forth two main findings to support their conclusion that EMU was the driver for stock markets integration in the Euro-zone: 1. the UK stock market does not show increase integration with the other European stock markets; and 2.financial integration is a Euro-zone-specific phenomenon, independent of world-market integration (p. 390).

Baele et al. (2004) examined the impact of EMU introduction on five types of markets in the Euro area: money, government bond, corporate bond, banking/credit and equity markets. Their findings indicated that the integration of each market has attained different levels: the money market is the most integrated whilst the equity market is the least integrated of the five types of markets in the Euro area. This outcome can be related to the study of Adjaoute and Danthine (2003) who also found that the equity markets in the Euro area are only partially integrated. They argued that EMU facilitated integration but that other barriers continue to exist for a truly integrated financial area to exist.

Choudhry et al. (2007) collected reasons for integration into three categories: the economic ties and policy coordination between countries; the real interest rate linkages between countries due to international capital flows, as real interest rates affect stock prices; and the increased importance of international investors. An excellent resume is given by Kim et al. (2005): '…integration of the financial markets is fundamentally linked to economic growth through risk sharing benefits, and reductions in macroeconomic volatility' (p. 2476.. See also Prasad et al. 2003).

However, the relationship between economic and financial integration is not always straightforward. For example, Bekaert and Harvey (2002a, p. 430) differentiated between economic integration, which is characterized by a decrease in barriers to trade in goods and services, and financial integration, which is related to the free access of foreigners to the local capital market and of local investors to foreign capital markets.

Another interesting difference is raised by Kearney and Lucey (2004) who noted that the pace of financial markets activities grows faster than the pace of real output. They also argued that the actions of international investors looking for the best risk-return investments in increasingly integrated financial markets have an effect on governments' ability to pursue independent policies.

> In particular, they impact directly and forcefully on the determination of exchange rates, they influence the levels of national income and employment, and they may eventually curtail the potential benefits of international diversification. (Kearney and Lucey, 2004, p. 572)

Empirical evidence regarding the relationship between economic and financial integration is mixed. For Cheng (1998), economic integration and stock market integration are closely related. Using factor analysis and canonical correlation, he first showed that the US economic cycles lead the UK's and the US economic indicators explained the variance in the UK economy. Then, looking at the relationship between the two stock markets, he found high co-movements as well as evidence of feedback relationships between the two markets. Overall, Cheng concluded that the US financial market and economy seem to have a stronger influence on the UK's than vice versa.

A similar approach and results were presented by Phylaktis and Ravazzolo (2002). Focusing on Pacific-Basin countries (PBC), they found evidence that economic integration provides a channel for financial integration. Moreover, the authors could not observe a difference in the degree of integration among countries even when they displayed different degrees of stock market openness during the nineties; restrictions such as foreign exchange controls seemed not to isolate capital markets from world influences. Finally, Phylaktis and Ravazallo, explained the high regional contagion effect of the Asian crisis with the important regional economic interdependence and the milder effect of the crisis on the global financial markets by the less important financial integration of the PBCs at the global level.

Cheung and Lai (1999) also looked at the relationship between economic and market integration, but their conclusions were different and contradicted both Cheng (1998) and Phylaktis and Ravazzolo (2002). Using cointegration they found that the French, German and Italian stock markets displayed long term co-movements. They attempted to explain this relationship with macroeconomic determinants including money supply, production and dividends. Here too, these variables were also found to be cointegrated. However, when looking at the relationship between common permanent components in stock prices and macroeconomic variables, the authors found that macroeconomic variables have a limited role in accounting for the relative stock market movements. They explained the results with the "missing-variable perspective", i.e. that the French, German and Italian stock markets co-movements could be influenced by economic variables other than the three macroeconomic determinants taken into consideration in their study.

Other authors tried to identify the legal or macroeconomic factors that may impact the financial integration. For example, Dickinson (2000) assessed the integration of the US, UK, French and German stock indices for the period 1980-1995. He found evidence of long run equilibrium between all but the US indices for the period 1988-1995 only. He attempted to explain this result with macroeconomic variables including: real interest rate, real exchange rate and industrial production. His findings showed that real interest rates explained the stock return variability best. However, the interaction seemed to be bidirectional: stock indices may affect real interest rates. He explained the latter finding by the fact that stock market performance can be seen as an indicator of future activity.

Chay and Eleswarapu (2001) looked at the impact of deregulatory reforms on the New Zealand stock markets: they wanted to assess whether the removal of direct barriers to capital flows lead to an increased degree of market integration. They found evidence that the New Zealand market was segmented before the reforms of 1984, with conditional returns only affected by domestic business conditions and more globally integrated following the reforms. Along the same lines, Chelley-Steeley et al. (1998) examined the impact of the removal of exchange controls, a direct barrier, on major European stock markets. They found evidence that the reform increased the interdependence between most of the European stock markets.

These findings contradicted Bekaert (1995) who insisted on the predominant role of indirect barriers, as he found that the correlation between integration and direct barriers to foreign investments (ownership restrictions and control of capital flows) is weak.

Bekaert and Harvey (2002a) argued that one has to be careful to distinguish between the concept of liberalization and integration. Focusing on emerging markets, they provided the example of a country that passes a law to seemingly drop all barriers to foreign participation in local capital markets. They argued that this might not be an effective liberalization measure. Foreigners might have had access to the market using other means or they might not believe in the new regulations. Therefore, integration is not directly related to liberalization measures. For the authors, integration is therefore a gradual process and the speed of the process is specific in each individual country, as it is unlikely that all barriers to foreign investments (legal barriers, access to information, economic policy risk, currency risk among others) disappear at the same time (on the distinction between market liberalization and market integration, see also Bekaert and Harvey 2002b).

Finally, Ayuso and Blanco (2000) also insisted on the fact that, parallel to the liberalization of capital movements, technological innovation has provided means to move huge amounts of capital quickly and safely across countries, so helping market integration.

3.3 Methods for Analysis of Market Integration

There exist many approaches to research market integration. Kearney and Lucey (2004) provided an interesting theoretical framework, linking definition and measurement of international financial market integration. Reviewing the literature on financial market integration, they classified the different approaches in two broad categories: direct and indirect measures.

In the direct measures, they included one approach related to the law of one price, according to which the rates of return on financial assets with similar risk characteristics and maturities should be equalized across political jurisdictions. The assumption being that, because of theoretically unrestricted international cash flows, seeking the best available return should lead to an equalization of returns across countries; i.e. "assets with identical cash flows should command the same return" (Kearney and Lucey 2004, p. 573). More specifically, using the covered interest parity condition (CIP), unrestricted international capital flows tend to equalize nominal interest rates across countries when they are contracted in a common currency. Ayuso and Blanco (2001) suggested that for the law of one price to hold, there should be perfect cross-market integration, i.e. a situation with no barriers of any kind to international financial transactions. If this is true, then there are no cross-market arbitrage opportunities.

According to Kearney and Lucey (2004), the main problem in applying this approach empirically is that of finding financial assets with similar enough risk profiles across countries for a meaningful comparison. Among their direct measures of integration, Kearney and Lucey also included the analysis of equity market correlations or the common stochastic trend in returns. However, these studies have the difficulty of testing ex ante expectations using ex post realized returns (p. 574). Moreover, disagreeing with the previous authors, Ayuso and Blanco (2001) argued that "the law of one price or the absence of arbitrage opportunities cannot be assessed from the analysis of the co-movement of the levels of financial asset prices or of their volatilities". (p. 269)

In the category of indirect measures, Kearney and Lucy (2004) included two approaches. The first one is related to the concept of international capital market completeness. According to Stockman (1988, cited in Kearney and Lucey 2004, p. 573) "financial integration is perfect when there exists a complete set of international financial markets that allow economic and financial market participants to insure against the full set of anticipated states of nature". The second indirect measure is based on the extent to which domestic investment is financed from international savings rather than domestic savings. This approach is related to perfect capital mobility whereby for a country that is small in world finance markets, exogenous changes in national savings can be financed from abroad, with no changes in real interest rates. It is directly related to the findings of Feldstein and Horioka (1980, cited in Kearney and Lucey, 2004) who stated that national savings and domestic investment correlate well. However, Kearney and Lucey do not believe that the correlation of these variables have implications for the degree of international cash flows. The authors concluded their review of the theoretical framework by proposing that the two most helpful definitions of financial market integrations are CIP and capital market completeness.

3.4 Consequences of Market Integration

In an article on emerging markets finance, Bekaert and Harvey (2002a) looked at the impact of market integration on security prices. Using the framework of the Capital Asset Pricing Model (Sharpe 1964; Lintner 1965), they explained that in a completely segmented market, assets are priced off the local market return: 'the local expected return is a product of the local beta times the local market risk premium' (p. 431). Because local returns exhibit high volatility, it is likely that local expected returns will be high. Now, if markets are integrated, then the expected returns will be a function of a beta estimated with respect to the world market portfolio multiplied by the world risk premium. In this case, the expected returns will be lower. Thus, theoretically, when a segmented market changes into an integrated market, prices should rise and expected return should decrease. To verify this statement, the authors examined the average annual geometric returns of 20 emerging markets, the International Finance Corporation (IFC) composite portfolio and the Morgan Stanley Capital International MSCI World market portfolio, for the period pre-1990 and post-1990. The 1990 breaking point is chosen as capital market liberalizations are clustered around that date. As expected, they observed a sharp decline of the returns for the post-1990 period. On the other hand, volatility measured as the average annualized standard deviation seemed not to be affected by market liberalizations: it increased for some countries and decreased for others. Recognizing that market integration is a gradual and complex process which is difficult to date exactly, they referred to studies applying more complex models but yielding essentially similar conclusions (for example: Bekaert and Harvey 2000; Kim and Singal 2000). Moreover, the authors insisted that emerging market returns remain not normally distributed for both periods: despite liberalization, markets are skewed and have fat tails.

In a similar spirit, de Jong and de Roon (2005) examined market integration of 30 emerging stock markets for the period 1988 to 2000 and using a time-varying beta to measure the gradual process. They found that the emerging markets have become more integrated with the world stock markets. According to their estimation, the segmentation decreases at an average annual rate of 0.055 on a scale $[0, 1]$. Similarly to Bekaert and Harvey (2002a), they argued that "integration with the world market leads to lower expected returns and hence lower cost of capital" (p.608). Indeed, they estimated that the decrease of segmentation induce an average decrease of 4.5% for the 30 emerging stock markets of the sample.

Bekaert and Harvey (2002a) also examined the impact of integration on market correlation. Interestingly, they believed that, in theory, integration should not necessarily lead to higher correlation with the world: ‘a country with an industrial structure much different than the world’s average structure might have little or no correlation with world equity returns after liberalization’ (p. 434). However, their research showed that on average, correlations of the emerging markets with the world market has increased post-1990, as well as correlation among emerging markets. They provided the same picture when estimating emerging markets beta with respect to the world market returns: for most of the markets, the beta increased during the post-1990 period.

An increase in market correlation might harm the benefits of international diversification. Indeed, stock market integration implies that markets are subjected to the same set of risk factors (Ahlgren and Antell 2004, Tahai et al. 2004). This can be an important drawback for international portfolio.

The modern portfolio theory (MPT) originally developed by Markowitz (1952) is based on diversification of risks which in a mean-variance framework is related to the correlation structure among assets: the lower the correlation among assets, the greater the diversification. Fundamentally, MPT asserts that an investor should look at the portfolio rather than at individual assets, as a portfolio will yield a higher return for a specific level of risk. More specifically, a portfolio allows for the reduction of unsystematic risk, the risk specific to each asset. A carefully chosen portfolio should leave the investor with only the systematic risk, the risk of the market. Asset allocation might include assets from different industries, as they will be less correlated with each other than assets coming from the same industry. But, when possible, investors should also choose assets from different countries, international diversification, as they are less correlated than assets from the same country, domestic diversification (Longin and Solnik 1995 ; Solnik 1974, reprinted in 1995). Of course, when including international assets in their portfolio, investors also expose themselves to potential exchange risks. They can choose to hedge and remove exchange risks by buying, for example, forward exchange contract. However, they may decide to keep their position unhedged and then also speculate on the currency. Solnik (1974, reprinted in 1995) compared the riskiness of three portfolios: one domestic comprised of only US stocks, one international unhedged and an international hedged portfolio. The domestic portfolio presented the highest level of risk, followed by the international unhedged and the international hedged portfolio. He concluded that the benefits of international diversification offset the risks of the non-protection against currency exchange.

Market integration has two consequences on stock markets relations: an increase in correlation and an increase of short and long term dependences. For Masih and Masih (2004), long-term equilibrium may have an impact and thus potential abnormal profit from diversification in cointegrated European markets is limited to the long-term. However, they did not rule out the possibility of profit from diversification in the short-term. Tahai et al. (2004) who assessed the degree of financial integration of G7 equity for the period 1978 to 1997 reached a similar conclusion. On the other hand, Bekaert and Harvey (2002a) argued that correlations of emerging markets' returns are still sufficiently low to provide opportunities for diversification.

In an interesting follow-up study, Solnik et al. (1996) investigated the relationship between volatility and international market correlations. More specifically, they raised two questions. Has market integration raised international correlation? Is correlation increasing in periods of high market volatility? The sample was comprised of weekly and monthly data for stocks and bonds of German, French, UK, Switzerland, Japan and US index during the period 1958 to 1995. They computed the standard deviation and correlation using a rolling window of 36 months. They found that an increase correlation between stock markets, in particular between France and the UK which they explained with the leading role these countries play in the EU. Moreover, they found evidence that international correlation increases in periods of high market volatility, which they assessed as bad news for the global money managers: "when the domestic market is subject to a strong negative shock is precisely when the benefits of international risk diversification are needed most, but the increased correlation reduces that benefit" (p.33). They concluded however that the benefits of international risk reduction are still robust.

Partially agreeing with Solnik et al. (1996), Karolyi (2003) believed that an increase in co-movements can be explained by two hypotheses. He claimed that co-movements can reflect innovations in common, i.e. unobservable global factors. However, he also argued that co-movements can be related to noise traders, where "increases in correlation especially around stressful, bear market periods, represent the work of uninformed investors who overreact to news in one market relative to another or who respond to shifts in sentiments regardless of fundamentals in those markets" (p. 191).

Other studies have presented an increase in predictability as an important consequence of market integration. Bhattacharyya and Banerjee (2004) who looked at the integration of 11 developed and emerging stock markets for the period 1990 to 2001 used the Granger causality test to assess the causal relationship between the markets. They found that the Hong Kong market led other Asian markets. A similar strategy was adopted by Huang et al. (2000). They also found that, for the period 1992 to 1997, the US stock market Granger caused the South China Growth Triangle region stock market. They concluded that US price changes could be used to predict changes in the Hong Kong and Taiwan markets. Similarly, Yang et al. (2003) used an impulse response function to evaluate the short-run dynamic linkage between the US and eleven Asian markets for the period 1995-2001. They found that the US market substantially influenced the Asian markets but was not influenced by them. Furthermore, it appeared that the Singapore market led the Asian region. Along the same lines, Masih and Masih (2004), using variance decomposition and impulse response analysis, demonstrated that the British stock market explained shocks in the French, German, Dutch and Italian stock markets.

Thus, market integration has impacted on the interaction of stock markets. It has tended to increase their correlation and their short and long-term relationships. Consequently, there is an increase in predictability between stock markets. This factor may affect portfolio diversification.

3.5 Empirical Models for Market Integration

The previous sections reviewed the definitions of market integration, the different approaches to research the trend, and the consequences on portfolio diversification. This section looks at different models developed to empirically research market integration. They mainly fall into the direct measures category proposed by Kearney and Lucey (2004). The presentation is divided into static and dynamic models. Static models, such cointegration, are estimated over one period and dynamic models, such as conditional correlation, try to capture the changes in each observation.

3.5.1 Market integration: static models

Markets integration was first researched using different approaches, such as spectral analysis to research markets' co-movements, or cluster analysis to look for correlation among equity markets (Tahai et al. 2004; Masih and Masih 2004).

An example of this approach can be found in Asimakopoulos et al. (2000). In their article, the authors analysed the interdependence of the US and some major European equity markets using spectral analysis. In this approach, each time series is first described in terms of its cyclical components and their relative importance: the univariate spectrum. Then the relationship between the different series is assessed by comparing the cycles of each series. The coherence spectrum is the equivalent of a square correlation in the time domain and estimates, within a frequency band, the percentage variance in one series that is predictable from another series. Finally, the phase spectrum looks at the phase relationship between series within each frequency: does the change in one series occur at the same time as in the other series or is there a lead/lag effect?

Assimakopoulos et al. (2000) used daily returns from the indices of the three largest European markets in terms of market capitalisation: London (FTSE 100), Franfurt (DAX 30), Paris (CAC 40); and the New York market (S&P 500) for the period 01/01/1990 to 31/10/1996. Analysis shows a high-level of contemporary correlation between the returns of the three European indices: 0.447 between DAX 30 and FTSE 100; 0.597 between DAX 30 and CAC 40; 0.618 between FTSE 100 and CAC 40. There is a lower contemporary correlation between the European indices and S&P 500 than among the European indices, but a stronger link between current European returns and lagged returns of S&P 500. This pattern translates the non-synchronous trading on the European and US markets. It also reflects the responses of the European markets to changes from the previous trading day in the US market. Univariate spectra for the four returns showed that the CAC 40 has the largest variance, followed by DAX 30, FTSE 100 and S&P 500 (in the time domain, the standard deviation showed the same finding). Moreover, the four indices presented similar patterns at low frequency with cycles of between 11 to 13 days duration. For the European indices, there is also an important cycle of duration of approximately four days. At higher frequency (shorter duration cycles), there is no clear pattern. Coherence analysis showed important correlation between the three European indices across the entire range of frequency. The highest coherence was between the CAC 40 and the DAX 30, a finding that the authors attributed to the high level of integration between the German and the French economies. When comparing the European and the US markets, the coherence is high at the lowest frequencies, but decreases rapidly beyond frequencies of about 1.5, corresponding to cycles of duration between four and five days. This indicates that there are some similarities between the US and European markets over the longer duration cycles (low frequencies), but less over the shorter duration cycles (one day to one week, higher frequencies). Moreover, phase spectra showed that within Europe, the DAX 30 had a tendency to lag both the FTSE 100 and the CAC 40 at all frequencies, whereas there was no clear pattern between FTSE 100 and CAC 40. Finally, the US market had a tendency to lead all the European markets. Asimakopoulos et al. explained the latter finding in terms of non-synchronous trading: 'the European markets respond to developments affecting the US after the close of the previous days- trading in Europe' (p. 46).

Another empirical tool used in the early literature is the correlation structure of the equity markets' returns. A predominant view is that if the correlation structure shows instability over time, then, assuming the trend is towards increased correlation, there is evidence of integration (Kearney and Lucey 2004, p. 575). Another view is developed by Kasa (1995 cited in Ragunathan et al. 2004) who believed that integrated markets should display a minimum level of correlation. His hypothesis states that if markets are integrated, then 'the unobserved stochastic discount rate in the two markets should be the same' (p.1168). This hypothesis was tested using the Hansen and Jagannathan's (1991) bound on the volatility of the discount factor which Kasa modified into the measurement of a lower bound on correlations: if markets' bilateral correlations fail to satisfy the bound, then markets are believed not to be integrated. In his initial study, Kasa limited his sample to three countries. Ragunathan et al. applied Kasa's methodology but extended the sample to 18 countries. Moreover, they decided to use two different proxies for the risk-free rate: one-month Certificate of Deposit (CD) and the US three-month Treasury bill rates. Their results demonstrated that the choice of the risk-free proxy had an impact on their findings. More specifically, the Sharpe ratios, used as the coefficient of variation in the calculation of the bound, are consistently lower if measured as an excess on one-month CDs than as an excess on three-month Treasury bill rates. The authors explained this fact by the risk premium included in CDs. Overall, Ragunathan et al. found evidence in favour of integration of the 18 countries with the US and the World markets.

Leong and Felmingham (2003) performed a similar survey. They looked at the co-movement of five major Asian stock markets around the Asian Crisis, using daily data for the period 1990 to 2000 and broke down the original sample into two sub-periods. They found that overall the correlation between indices has strengthened since the Asian crisis.

Unconditional correlation structure as a measurement of market integration has been criticized. Ayuso and Blanco (2001) pointed out that higher correlation is neither a necessary nor a sufficient condition for greater market integration:

> If markets are completely integrated and, therefore, there are no arbitrage opportunities, returns on different assets can be divided into a common component and an idiosyncratic one. The latter, however, maybe sufficiently important as to render ex-post correlation rather low. (Ayuso and Blanco 2001, p.266)

To illustrate their points, they estimated the correlation structure of seven stock exchanges (New York, London, Paris, Madrid, Frankfurt, Milan, and Tokyo) for the period 1995-1999. On average, correlation between these markets was 0.54. During the same period, they analysed the correlation between seven sub-indices of the New York Stock Exchange and found that, on average, it was 0.47. Arguing that it was not reasonable that the degree of integration should be higher across stock exchanges than within any of them, they concluded that the static correlation approach is flawed. Increased correlation provides evidence of increased financial market linkages, not higher integrations. (Ayuso and Blanco 2001).

A popular approach that can be included in the static model is cointegration analysis. Kearney and Lucey (2004) noted that cointegration has an intuitive appeal to assess integration. If equity markets are integrated, then stock prices are expected to have long-run relationships, i.e., they share common stochastic trend(s). Therefore, cointegration is a method often used, as it helps to capture long-term relationships and provides understanding of short-run market interaction using the error correction models (see also Choudhry et al. 2007; Masih and Masih 2004).

The remainder of this section is organised as follows: first the concept of the cointegration analysis and related techniques are presented, and then three applications which exemplify the use of the cointegration analysis in stock markets are discussed in detail.

<u>Testing for cointegration:</u>

Different tests for cointegration exist, but the method developed by Johansen, and its various improvements, is very popular in the literature (Ahlgreen an Antell 2002, p. 851).

Evidence of cointegration between markets can be interpreted differently. Dickey et al. (1994 cited in Ahlgreen and Antell 2002) explained that cointegrating vectors can be thought of as representing constraints that an economic system imposes on the movement of the variables in the system in the long-run. Consequently, the more cointegrating vectors there are, the more stable the system. For Bernard (1991 cited in Kearney and Lucey 2004, p. 576), a necessary condition for complete integration is that there are $n-1$ cointegrating vectors in a system of n indices.

Some authors (Choudhry et al. 2007; Granger 1986 cited in Huang and Fok 2001; Baillie and Bollerslev 1989 cited in Ahlgreen and Antell 2002) argued that if markets are cointegrated, potential prediction of future stock prices based on past returns is possible. This would be in breach of the efficient market definition which states that stock prices are unpredictable. Other authors (Baffes 1994; Engel 1996) rejected this idea as they understand EMH as ruling out arbitrage opportunities from prediction returns rather than stock predictability return. For example, Misah and Misah (1999, 2004) also believed that cointegration does not necessarily mean inefficiency and that an inefficient market exists only when predictability can lead to risk adjusted excess returns. In the same vein, Climent and Meneu (2003) explained that incompatibility between cointegration and efficiency depends on the definition of efficiency. If an efficient market is defined as a market without arbitrage, then cointegration between markets alone does not imply inefficiency, but rather the existence of abnormal returns yielded from the cointegration predictability. Moreover, Chelley-Steeley et al. (1998) argued that cointegration among European indices allowed prediction of only a small proportion of the variation of the equity markets they surveyed. For Dickinson (2000), cointegration between stock indices alone is not a sufficient analysis:

> …international stock index co-movement seems to depend upon more general financial market linkages than is apparent from an analysis of stock index cointegration alone and that equivalently international linkage extend beyond interaction between stock indices. (p.273)

Finally, Kasa (1992) questioned the fact that cointegration reflects the integration of stock markets. He argued that stock market prices can be cointegrated for other reasons than stock market integration.

A popular methodology to assess the relationship between markets is therefore based on multivariate cointegration, impulse-response function (IRF), and forecast error variance decomposition (FEVD), capturing both long and short run dependence between series. More specifically, the cointegration analysis looks at potential long run equilibrium between variables, IRF reflects to what degree the shocks in the variables are transitory, or persistent, and FEVD evaluates the relative importance of random changes in the explanation of the FEVD of the returns of other variables (For a good overview of the approach, see Climent and Meneu 2003).

Evidence from cointegration analysis in stock markets:
Presented here are three examples of research following the above approach (for more examples, see also Masih and Masih 1997; Cheung and Lai 1999; Dickinson 2000; etc.).

The aim of Masih and Masih (2004) was not to measure directly market integration, but to assess the dynamic linkages among five European stock markets and the effect of the October 1987 crash on their transmission mechanism. The data for the research is comprised of end-of-month closing share price indices for the French, German, Dutch, and United Kingdom stock exchanges for the period January 1979 and June 1994. To account for the October 1987 crash, the original sample was divided into two panels (pre-crash: January 1979 to September 1987 and post-crash: November 1987 to June 1994). Moreover, the raw indices have been transformed into real US dollars in order to adopt the point of view of US investors, but also to damp out 'the noise from exchange market fluctuations upon stock price without distorting the exchange rate influence upon stock markets' (p.5). The Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) tests showed that the series were integrated of the first order, $I(1)$. The Johansen-Juselius (JJ) test for multiple cointegration indicated that there existed at most a single cointegrating vector in each of the models over the pre and post-crash samples. However, the null hypothesis of no -cointegrating vector for the entire sample period could not be rejected. Using the Vector Error Correction Model (VECM) and the Granger (1969) causality test to model the short term linkages among the stock markets, they discovered that the lead-lag relationships changed from the pre- to the post-crash panels. During the pre-crash period, short-run changes in the German index Granger caused changes in all other indices, except for Italy. Likewise, the French and the Dutch indices have the same causality on the Italian and the United Kingdom indices respectively. For the period after the crash, the picture changed: the relationship between the German and the United Kingdom was inversed, with UK now leading the German index whilst the German continued to lead the French market, but all other causal linkages disappeared. Information from the Error Correction Term (ECT) indicated that in the pre-crash period, changes in the German and French indices adjusted in the short-run for the deviation from the long-run equilibrium, and in the post-crash period, it was the French and the Italian indices that bore the brunt of short-run adjustments. Finally, the main finding from the impulse response and variance decomposition analysis was that, especially for the post-crash period, the UK and Dutch market had a leading role in picking up information and passing it to the rest of the market. Masih and Masih explained the leading role of the UK market by the fact that it had high liquidity and capitalization and low transaction costs, but also an independent monetary policy. This explanation did not hold for the Netherlands that had low absolute capitalization. However, compared to the other four markets, it had a high equity capitalization to GDP and the highest proportion of foreign firms listed. Masih and Masih noted that temporal causality and the propagation mechanism among stock markets should be addressed 'in a multivariate and, if possible, cointegrated framework, particularly since the fluctuations in the financial markets are so interactive and interdependent'. (p.21)

Another representative example of this methodology can be found in Climent and Meneu (2003), who researched whether the 1997 Asian crisis increased information flows between international markets. They used daily stock indices prices for 7 South East Asian major markets, the UK, Euro-zone, North America, and Latin America, for the period January 1995 to May 2000, and dividing the original sample into two subsamples (Pre- and Post-crash). They applied two multivariate cointegration procedures, a parametric approach (Johansen 1988) and a nonparametric approach (Bierens 1997). The results from both tests showed noncointegration between the 7 Asian markets and each of the major international stock markets, in both subperiods. The authors explained the results with the high number of markets and the small sample period.

However, Climent and Meneu (2003) argued that the absence of a long-term relationship does not imply the lack of short-run dynamics among the markets. Using a Vector Autoregressive (VAR) model, they first examined bivariate Granger Causality (Granger 1969) between the Asian series and the international markets. They found that in the pre-crash periods, the US, as well as the Latin markets, influenced all the Asian markets, except South Korea, but in the post-crash periods, all the international markets showed unidirectional causality towards the South East markets, except for Malaysia. According to the authors, South East markets displayed a greater dependence to information flow from international markets after the crisis. Willing to explore further the dynamics of these relationships, Climent and Meneu (2003) then applied an impulse-response function (IRF) and forecast error variance decomposition (FEVR). The results showed that during the pre-crash period, Asian markets responded from a shock from the US market, while during the post-crash period, the Asian market's response from a US shock grew. Moreover, the responsiveness of all international markets from a US shock seemed relatively more important, and all international markets, including the US, displayed a strong response to shocks from Asian markets. Climent and Meneu concluded then the degree of integration between the markets increased after the crisis. Finally, the results of the

FEVR underlined the exogeneous character of the US market, as well as its explicative capacity to events in the Asian markets. Overall, during the post-crash period, most of the markets reduced the explicative capacity of their own forecast error deviation variance which, according to the authors, translated the contagion effect of the crisis.

Choudhry et al. (2007) applied a slightly different methodology. The scope of their article was to assess the impact of the Asian financial crisis on the relationship between nine major Asian and the US stock markets. Their sample was comprised of the daily prices for the main index in each market for the period 1988-2003. They divided their original sample into three sub-periods: the pre-crisis, the crisis, and the post-crisis periods. In order to assess the long-run relationships between the markets, they applied the Johansen multivariate cointegration analysis. For each sub-periods, they perfomed three tests: one excluding Japan and the US in the VAR, one including Japan in the VAR, and one including the US in the VAR. This approach allowed them to separately assess the importance of Japan or the US on the other Asian stock markets. They found evidence of long-run relationships in each of the sub-periods, but the crisis periods included the highest number of nonzero cointegrating vectors. The authors argued therefore that diversification and minimising portfolio risk was harder during that period. More specifically, they argued that "including the Japanese or the US index in a portfolio of Far East stock markets may not help reduce portfolio risk" (p. 252).

The originality of the paper of Choudhry et al. (2007) is that they decided to assess the short-run relationship in the frequency domain rather than in the time domain, using the Band spectrum regression (BSR). The reason for not investigating the short-run interactions using a classic error correction model is that it depicts only one-step forward. However, the authors wanted to research the interactions of the market at different cycles: "the most attractive element of BSR is its ability to discriminate between the long-run and the short-term relationship among variables" (p.254). Indeed frequency domain can separate different frequency bands corresponding to specific time periods. Their results showed an increased influence of the US and Japanese index on the Asian markets during and after the crisis.

3.5.2 Market integration: dynamic models

You and Daigler (2010) showed that using constant correlation measurements to model the relationship among international stock indices is too simplistic. They computed the constant correlation between 15 stock indices then tested their stability, applying the Tse (2000) test. The results indicated that 50% of the pairwise correlations were not constant at the 15% significance level or above. They therefore advocated the usage of the Dynamic Conditional Correlation (DCC), as developed by Engle (2002), to capture the time-varying nature of international stock market correlations.

Similarly, Kim et al. (2005) questioned the use of cointegration based models to assess integration. They argued that the long-run stable relationships assumed by cointegration analysis are not suitable to capture the dynamic process of stock market integration as the process is not complete and exhibits strong variation over time. Moreover, they proposed that this model looks at the existence of an equilibrating process and not the forces behind the long-run equilibrium. In the words of Bekaert and Harvey (2002a, p. 441): 'our theoretical models are characterized as static models of integrated / segmented economies. The true process is dynamic and much more complicated than our current models'.

Similarly, Kearney and Lucey (2004) believed that the main weakness of the static models which focus on comparative statistics is that they do not take into consideration time variation in equity risk premia, an important element of asset returns. For example, Chue (2002) argued that time-varying investor risk preferences impact on shocks transmission across international financial markets:

> …when emerging markets become increasingly integrated internationally, domestic equity returns can be affected by foreign shocks which do not directly hit the home market, but affect the common stochastic discount factor that prices all assets in the integrated international market .(p.1069).

Indeed, even studies using static models recognized that the degree of integration among markets is not static but tends to move over time, especially during a financial crisis. For example, Yang et al. (2003) and Roca and Bunsic (2002), looked at the impact of 1997-1998 Asian financial crisis, Dickinson (2000) and Masih and Masih (2004) focused on the European stock markets during the October 1987 crash. They all found evidence that the relationship between markets changes over time. By the same token, Chatrath et al. (1997) examined the long run relationship of the national prime rate and the negotiable CD rates for six industrialized countries. Whilst they found evidence of integration in bank lending and borrowing markets, the nature and the strength of the results are related to the time period investigated.

Therefore, the approach taken to recognize the dynamic characteristics of the processes while analyzing them with a static model is to divide an original sample into subsamples (see Yang et al. 2003; Roca and Bunsic 2002; Dickinson, 2000; Masih and Masih 2004; Climent and Meneu 2003, Phylaktis and Ravazollo 2002; Choudhry et al. 2007). This is the method adopted by Bracker et al. (1999). The scope of their study was to investigate how and why different pairs of national equity markets exhibit different degrees of co-movement over time. The data were daily national stock indices for nine countries: Japan, Australia, Hong Kong, Singapore, Switzerland, Germany, UK, US and Canada. The sample was 22 years (1972 to 1993) and was split into 22 subsamples of one year each. They applied the Geweke (1982) measures of feedback for each of the 36 possible pairs in order to assess the nature (contemporary, lead or lag) of the relationship of the returns and how they vary over time. Their analysis took into consideration non-synchronous trading across markets. Their results showed important co-movement across all eight pairs of markets within the same day (24 hours period) in all 22 years of sample. These measures tend to increase over the year, indicating a strengthening of co-movements. Lead-lag relationships among returns seemed overall weaker, with the US more likely to lead other markets than vice-versa. The author concluded that this lead is the translation of the US leadership in capital, goods and services global markets, as well as in the global political arena (p.14).

However, all the above examples remain based on static models. Interesting examples of the application of time varying models can be found in the articles of Kim, Moshirian and Wu (2005, 2006). In the first article, the authors looked at the stock market integration driven by the European Monetary Union (EMU), and in the second they looked at the integration of stock and bond markets under the influence of the EMU.

In Kim et al. (2005), the sample is comprised of the national price indices of the twelve Euro zone members (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain), the three non Euro-zone European countries (Denmark, Sweden, the UK), and Japan and the US. They used the daily prices from 2 January 1989 to May 2003 and computed the local currency returns as they wanted to research the impact of the changes in exchange rate risk induced by the introduction of the Euro; the daily frequency being important to track down co-movements in equity returns. They also estimated stock market returns for the Euro-zone (regional return index) as the market value-weighted average return of the twelve EMU members. However, when estimating a bivariate model including the regional index and an EMU member's index, the regional returns were computed exclusive of that EMU member, in order to filter out idiosyncratic market shocks in the regional return index. Descriptive statistics showed that all returns were non-normal, exhibiting skewness and excess kurtosis. The Ljung-Box Q test presented evidence of linear and non-linear serial correlation in all return series and the presence of heteroscedasticity. To assess the impact of the currency union on stock market integration, they estimated bivariate ARMA (p, q) EGARCH (1,1) models. The parsimonious ARMA (p,q) model captures the dynamic mean stock returns for each individual country and the Euro-zone and the EGARCH model includes the interdependencies in the innovations. The results of the bivariate Ljung-Box Q test showed that ARMA-EGARCH-t models captured successfully all joint linear and non-linear serial correlations in the returns. Moreover, using the EGARCH models, the authors estimated conditional correlation between national markets and regional markets.

The results of the conditional correlations showed that the integration of the EU countries varied over time and was volatile for the period prior to mid 1990s. The European Monetary System (EMS) crisis pushed stock markets towards further segmentation. However, during the period 1996-1997, the trend changed towards integration. The authors noted that this period coincided with the Treaty of Amsterdam, which amended and reinforced the Maastricht Treaty. The period beginning in 1999 showed a further integration with a damped volatility in all conditional correlation, a fact that the authors related to stabilization in macroeconomic fundamentals through EMU convergences process. However, conditional correlations did not show the same pattern of co-movements between the Euro-zone and the non Euro-zone markets.

To further research the relationship between the markets, Kim et al. (2005) split the original sample into three sub-samples: a. 1989 to 1995 (period before major changes in integration process of equity markets); b. 1996 to 1998 (period of intense pre-Euro integration); and c. 1998 to 2003 (post-Euro period), and looked at the mean and volatility spillover effects. They discovered that linkages between all stock markets under scrutiny strengthened with the currency unification, return and volatility spillovers increased in most of the countries in the period of the introduction of the Euro. Moreover: 'the significant spillover coefficients indicate the EMU members are crucial both to each other's and to the stability of the world economy as a whole' (p.2489).

Using a similar approach, Kim et al. (2006) examined the dynamic change in inter-stock-bond market integration for the period 2/3/1994 to 19/9/2003. Data included daily national market return indices and total return government bond indices (bonds with more than 10 years to maturity) in local currency for France, Germany, Italy, Spain, UK, Japan, and the US. They also estimated a value weighted average for the Euro zone. The original sample was divided into two sub-samples: a. 1994 to 1998 and b. 1999 to 2003.

The result of conditional correlation analysis between stock and bond markets showed that, at the country level (inter market integration), the markets tend to be segmented, especially after the mid-1990s. Exceptions are Italy and Japan, which exhibited respectively increases in conditional correlation and negative correlation. However, when estimating conditional correlation between a country stock or bond market and the respective EMU value weighted market (intra market integration), the findings are quite different. Beginning in 1997, the European stock markets exhibited a high conditional correlation, indicating integration, and the US and Japan a lower but increasing conditional correlation. Likewise, the four EMU bond markets, as well as the UK bond markets, are highly correlated with the Euro zone regional bond index (ranging from 0.65 to almost 1). The US has a lower conditional correlation (0.68 to 0.75) and Japan a smaller correlation (0.03, -0.09). So, while the inter-stock-bond market integration has decreased at the country level, the intra-stock-bond market integration with EMU has strengthened. According to the authors, the introduction of the monetary union has Granger caused the segmentation between stock and bond markets within Europe.

Bartram et al. (2007) examined the impact of the introduction of the Euro on the integration of European financial markets. They used daily prices for the main indices of seventeen European countries, out of which twelve were from the Euro-zone, for the period 1994-2003. They assessed the stock markets' interactions applying time-varying copula dependence model. They observed that market dependence in to Euro area increased only for countries with large equity market capitalization, comprehensive regulations, high liquidity and low transaction and information costs. They found that this increase in dependence started in the 1997 and 1998, when the Euro was first announced. Also, they argued that the countries not members of the Euro-zone lack of integration with the Euro area. They concluded noting that the Euro increased financial market integration in the Euro area, but that these markets are not fully integrated.

3.6 Summary

Stock market integration is an important trend in finance. There are many definitions of market integration, but they all revolve around the concept of co-movements between markets.

Stock market integration is related to economic integration as the latter is believed to facilitate the first. Indeed, economic ties between countries, coordination of economic policies and linkages in the interest rates facilitate financial integration. The European Union, which includes political, legal and economic integration, the close relationship between the US and UK economies, and the PCB economies are examples often put forward in the literature. Parallel to economic integration, the development of technologies and their applications in financial trading are also important factors.

However, the relations between economic and financial integration are complex. For example, the actions of international investors can influence economic policies. Moreover, when tested, most of macroeconomic variables, except interest rates, seem not to have significant effects on financial integration. Finally, liberalization with measures of deregulation, decreases in barriers to trade and capital controls, is a gradual process. Moreover, it is difficult to ascertain which measure is more effective.

Financial integration impacts on stock market interactions. Their correlation increases and they exhibit short and long-term relationships. There is an important debate in the literature that looks at the impact of financial integration on portfolio diversification. Some argue that the increase in predictability reduces the advantages of the portfolio. Others believe that this predictability is not sufficient to attenuate the benefits from international diversification.

There are numerous approaches to investigate financial integration. One interesting taxonomy arranges them into two categories: the direct and indirect measures. The first category includes approaches which look directly at assets, such as the law of one price, equity markets correlation and common stochastic trends. The second category is comprised of methods that assess financial market integration indirectly, for example capital mobility.

Finally, the chapter ends with a review of methods to investigate financial integration. It includes mainly methods related to the category of direct measures. Another interesting taxonomy classifies the tools used in these methods into static and dynamic models. The tools of the first category estimate the models over the whole period and have difficulty in capturing the potential changes within the period. On the other hand, the tools from the second category look at the changes in each observation. Cointegration analysis is therefore a static model and conditional correlation a dynamic model. As financial market integration is a dynamic process, tools from the second category are seen as more appropriate. However, when static models are used, then the original sample needs to be divided into subsamples in order to capture the expected changes in the markets interaction.

3.7 Implications of the Literature Review for the Second Research Objective

The second research objective is to assess whether Euronext integration has increased the interaction between the three stock markets, i.e. it has increased the markets' integration.

Stock market integration is an important debate in finance. However there is no common definition of the pattern. This study understands market integration as an increase in co-movement between markets. Other definitions are attractive but their complexity makes them difficult to test.

On a methodological point of view, static and dynamic models have advantages and disadvantages. The articles reviewed generally adopted one type of methodology - for example, the static cointegration test, eventually followed by an error correction model, impulse response and variance decomposition. Another approach in the literature is to apply a dynamic correlation model. An interesting methodology for the second research objective may be therefore to include two types of models, cointegration (static) and conditional correlation (dynamic), yielding a robust testing framework.

4 Methodology

4.1 Introduction

This chapter addresses the philosophical and methodological foundations of this research. It first investigates the issues of the research paradigm, approach and strategy. Each issue is discussed with reference to the econometric methodology adopted in this study. A positivist philosophy, including a deductive approach and empirical research, is identified as suitable, but alternatives are also considered. The chapter ends with a discussion on how to minimise risks of reliability and validity.

4.2 Research Paradigm

The definition of a research paradigm or research philosophy is central to the research process as it is a description of the “world view” followed by the researcher. It therefore influences what should be studied, how it should be done and how the results should be interpreted (Bryman and Bell 2003, p. 23).

4.2.1 The positivism paradigm and its assumptions

The broad research paradigm adopted in this study is positivism. This research philosophy has its roots in natural sciences and was adopted by the social sciences in the nineteenth century. It assumes that the social reality is independent of the researcher. “According to positivists, laws provide the basis of explanation, permit the anticipation of phenomena, predict their occurrence and therefore allow them to be controlled” (Collis and Hussey 2003, p. 53). Saunders et al. (2003, p. 103-104) explain that positivists work with observable social reality and the results can be law-like generalisations. The research strategy usually comprises the use of theories to develop hypotheses, the collection of data, the testing of the hypotheses that will in turn lead to further development of the theories. However, Bryman and Bell (2003) argue that it is difficult to clearly define positivism as the views of authors often diverge. If the central approach is to apply the methods of natural sciences to the study of social reality, the term positivism can also entail different principles. In the words of the authors, these are:

1. Only phenomena and hence knowledge confirmed by the senses can genuinely be warranted as knowledge (the principle of phenomenalism)

2. The purpose of the theory is to generate hypotheses that can be tested and that will thereby allow explanations of laws to be assessed (the principle of deduction).
3. Knowledge is arrived at through the gathering of facts that provide the basis for laws (the principle of induction).
4. Sciences must (and presumably can) be conducted in a way that is value free (that is, objective).
5. There is a clear distinction between scientific statements and normative statements and a belief that the former are the true domain of the scientist. (Bryman and Bell 2003, p. 14).

Furthermore, Bryman and Bell (2003) also emphasize that positivism is not synonymous with science, as philosophers of sciences and social sciences have different understandings of scientific practice.

The positivist paradigm is based on several assumptions. The ontological assumption is that there exists a singular and objective reality, separate from the researcher. The epistemological assumption, the relationship of the researcher to that being researched, is that the researcher is independent from that being researched. The axiological assumption is that the research process is value-free and unbiased. The rhetorical assumption, the language of research, is formal and based on set definitions. Finally, the methodological assumption, the process of research, is based on a deductive causal process, with a static design. (Collis and Hussey 2003, p. 48-51).

4.2.2 Evolution of positivism

Classic positivism appeared in the 19th century. Auguste Comte (1798-1857), its founder, believed in discovering laws that can be established through observation, experiment and comparison. He introduced the methods of natural science to those of social sciences. In the 1920's, the Vienna Circle developed logical positivism, which insists on the importance of the experience as the base of knowledge and the use of logical analysis.

An important development of positivism is Popper's "falsificationism". According to Popper, we should not accept theories because they benefit from numerous types of supporting evidence, but reject the theories that are falsified. Therefore, all theories are tentative and cannot be accepted as absolutely true. When applied to the field of econometrics, Hoover (2005) presents two problems generated by Popper's approach. The first one is at which critical value should a theory be rejected as false? By nature, this is a technical question, but in this context, it can be seen as a conceptual one. The second and most important problem is, before being rejected, which theory should we use?

An answer to Popper's falsificationsim is given by Lakatos's Methodology of Scientific Research Programmes (1970). According to Lakatos (1970), Popper's view to reject a theory that is falsified is useless because all theories are falsified to some dimension. Instead, Lakatos proposes to assess a research programme both by what it explains and by what it fails to explain. Therefore, one programme is superior to another when it explains the anomalies of the other and predicts more novel facts.

As described in the next section, the empirical work developed to address the research objectives of this study uses quantitative data and econometrics. According to Hoover (2005), "most econometricians are positivists in the very broad sense of finding the source of scientific knowledge in either logical deductions from secure premises or in empirical observation" (Hoover 2005, p. 34). More specifically, he believes that logical positivism and its variants represent the main philosophical framework for econometricians. Hence, this study adopts the positivism research paradigm.

4.2.3 Alternative research paradigms

An alternative research paradigm for this research could be interpretivism. For this world view, the ontological assumption is that the world is not separated from the researcher and that there is no objective reality. Moreover, the epistemological assumption is that the researcher is not independent from what is researched. Instead of collecting 'real data', the researcher focuses on analyzing feelings and attitudes, and therefore researches social phenomena. Saunders et al. (2007, p.102-103) describe the researcher as a 'feelings researcher' in this paradigm, compared to positivism's 'resources researcher'. Consequently, the axiological assumption is that the research process is not value free and may be biased. Finally, the rhetorical assumption is less formal than in the positivist paradigm and the process of method will tend to be more inductive in nature.

Finally, Saunders et al. (2007, p.110) noted that the choice between positivism and interpretivism is not always clear, in particular the debate between the different epistemology and ontology positions. In certain cases, a pragmatist paradigm may be adopted. In the pragmatist framework, the most important determinant for the choice of the research paradigm is the research objective or question. Related to the pragmatist paradigm is the mixed approach, which allows a researcher to use the quantitative and the qualitative approach in the same study.

An interpretivist or pragmatist paradigm is more suited for a research in Behavioural finance as the scope is often there to research social phenomena rather than analyse hard data.

4.3 Research Approach

There are two general approaches to reasoning which may result in the acquisition of new knowledge: inductive reasoning, which is a theory building process; and deductive reasoning, which is a theory testing process.

4.3.1 Deductive approach

In line with the research paradigm of this study, the research approach is deductive reasoning. Deductive research calls for the development of a theoretical framework prior to its testing through empirical work using quantitative tools (Saunders et al. 2007, p.117-118; Bryman and Bell 2003, p. 9-10).

Robson (2002 cited in Saunders et al. 2007, p.117) presents five classic stages through which deductive approach will progress:

1. Deducing a hypotheses from the theory,
2. Expressing the hypotheses in operational terms,
3. Testing the operational hypotheses,
4. Examining the outcome: either it confirms the theory or indicates the need for a change in theory,
5. If necessary, modifying the theory in the light of the findings.

A deductive research approach is therefore characterized by a highly structured methodology, which allows for replications, and typically the use of quantitative data. Moreover, the scope of the researcher is to verify or modify existing theory and to generalize the outcomes from the research.

In this study, the testable hypotheses are drawn from the theoretical framework presented in the literature review and the quantitative approach will be based on the use of econometrics.

4.3.2 Econometric methodologies

Econometric methodologies can differ on two main points: the importance of the economic theory and the approach towards statistical procedures.

In an interesting article comparing the methodologies used by statisticians and economists, Granger (2001) describes 'econometricians as statisticians who concentrate on economic data' (p. 8). For him, statisticians are more data driven than theory driven, assuming that all valuable information lies in the data rather than in the theory. Moreover, statisticians see the observable world as stochastic while economists tend to believe it is deterministic. Furthermore, the aim of research for statisticians is to identify and understand data generating processes, which can only be approximated from data sets, and not to search for a generic truth, an approach closer to economists. Granger therefore concludes that the methodologies used by the two groups can diverge on the attitudes towards the data and towards the correctness of theory (p. 14).

Spanos (1999) has a slightly different point of view. For him, theory plays a major role in econometric research. In statistical inference, the use of a set of data to derive conclusions about a stochastic phenomenon can be seen as an inductive procedure. Spanos insists on the fact that 'this inductive procedure is embedded in a fundamentally deductive premise' as 'the procedure from the postulated model (the premise) to the inference propositions (estimation, testing, prediction, simulation) is *deductive*' (p.16, italic in the text). He therefore recommends that no conclusions should be based on statistical inference before the statistical adequacy of the postulated model has been established first (p.17). Moreover, for Spanos a statistical model is built exclusively in terms of statistical information whereas an econometric model is a synthesis of the theory and statistical model (p. 20).

The use of econometrics to test theories can follow two main approaches. The first, the theory-of-errors, assumes a one-way relationship from theory to data: the underlying theory is presumed to be true and the strategy adopted is to model the error terms. Hoover (2005) calls this approach "econometrics as measurements".

The second approach, which Spanos (1995) refers to as "probabilistic reduction", "…posits that a complete and true theory necessarily induces desirable statistical properties in the data: independent, serially uncorrelated, white noise. The scope of econometrics is therefore to find compact representations of the data that deliver these properties without loss of information. These representations are the statistical regularities that theory must explain" (Hoover 2005, p.22). This approach allows for a two-way relationship between theory and data.

An important development of the probabilistic reduction is the London School of Economics (LSE) approach. It is based on the idea of encompassing which assumes that one specification encompasses another if it carries all the information of the other specification in a more parsimonious form. In this view, the specifications are maintained only tentatively. An application of encompassing is Hendry's general-to-specific strategy which calls for starting from a very general specification (the General Unrestricted Model, GUM) and systematically reducing it to the most parsimonious specification, testing the statistical properties of the errors at every step. This strategy is therefore very close to the essence of Lakatos' paradigm.

Important criticisms of the general-to-specific approach are data mining and the large number of sequential tests which are not always interpretable (Faust and Whiteman 1995, 1997 cited in Hoover 2005). However, the danger of data mining appears to be higher if the researcher adopts the simple-to-general rather than the general-to-specific approach, as the first approach starts the research process from a simple model and adds variables until the specification appears adequate (Verbeek 2004, p. 57; Charemza and Deadman 1992). Furthermore, the supporters of the general-to-specific also argue, using a theorem of White (1990 cited in Hoover 2005, p. 26) that, given enough data, only the true specification will survive a set of tests. In fact, they assume that the ‘true specification’ is a special case of the General Unrestricted Model (GUM), the starting point of their research (Verbeek 2004, p. 57).

This study follows Spanos’ recommendations. The general-to-specific approach is adopted and the aim of the statistical model is to describe data generating processes parsimoniously. Moreover, theory and statistical models are used to build an econometric model.

4.3.3 Alternative research approach

Related to the interpretivist paradigm, an alternative research approach for this study could be the inductive approach. In this approach, the data lead to theory. If the positivism paradigm and the deductive approach are related to natural sciences, interpretivism and the inductive approach are closer to 20th century social sciences (Saunders et al. 2007, p.118). Consequently, the inductive approach is not only concerned with events, but with the context within which these events take place. Typically, it is characterized by a less rigid methodology which helps capture the uniqueness of context, as well as alternative explanations for events. Furthermore, the data used will tend be qualitative rather than quantitative. The scope of induction is therefore less to replicate an experiment and generalize conclusions than to provide a satisfactory understanding of a context.

Finally, as mentioned in the previous section, a researcher who follows the pragmatist paradigm usually adopts a mixed approach. In this framework, a researcher would use both inductive and deductive approaches and the choice of the approach is a direct function of the nature of the research question or objective addressed.

An inductive/qualitative research framework is therefore more related to Behavioural finance research whose scope is to discover the complex nature of the market and market participants.

4.4 Research Strategy

For the purpose of this study, empirical research is adopted. This approach focuses on establishing the relationship between variables (Ryan et al. 2002). Though similar to an experiment, as it involves hypothesis testing and control, the adopted strategy can be characterised as quasi-experimental because a direct manipulation of the independent variables by the researcher is not possible.

As mentioned in the introduction, the scope of this research is twofold and two research objectives were stated: 1. to test the information efficiency of the French, Belgian and Dutch exchanges before and after Euronext integration; and 2. to assess the level of market integration between the three exchanges before and after the Euronext integration.

Chapter two and three presented a review of the literature for these objectives. The outcomes of these reviews are instrumental in the design of the research strategy and the statement of the hypotheses. Sections 2.5 and 3.7 relate the outcomes of the literature review to the research objectives. Specifically, for the first research objective, the EMH paradigm is adopted as the theoretical framework and the methodology developed to address the objective is based on an algorithm widely used in the literature. For the second objective, market integration defined as increase in markets co-movements is the framework and a methodology including two types of model, a static and a dynamic, is adopted.

The empirical research is therefore comprised of two main parts, each addressing a research objective. The following sections introduce only briefly the research designs for each research objective; a more detailed description of the methodology is presented at the beginning of each chapter.

4.4.1 Data

As it is not possible to research the entire markets, the national indices are used as proxies for the markets. Therefore, the data used in this research are the daily adjusted closing prices for the main index of each stock market: the French CAC40, Belgian BEL20 and Dutch AEX. The period considered runs from January 1990 to December 2010.

As explained in the introduction to the thesis, the general principles behind the computations of these indices have not changed with the integration of the Euronext.

These indices are therefore reliable measurements to track the behaviour of the market during the whole period. Indeed, for all three indices, the calculation of the price index is based on the following general formula:

$$I_t = \frac{\sum_{i=1}^{N} Q_{i,t} F_{i,t} f_{i,t} C_{i,t} X_{i,t}}{d_t}, \qquad (4.1)$$

Where

t Time of calculation,

N Number of constituent equities in index,

$Q_{i,t}$ Number of shares of equity i included in the index on day t,

$F_{i,t}$ Free float factor of equity i*,

$f_{i,t}$ Capping factor of equity i*,

$C_{i,t}$ Price of equity i in time t,

$X_{i,t}$ Current exchange rate in time t*,

d_t Divisor of the index in time t,

*Factor is equal 1 if not applied for the index.

For all three indices therefore, the calculation is based on the current free float market capitalisation divided by the divisor. The divisor is determined by the initial capitalisation base of the index and the based level. It is adapted as a result of corporate actions and composition changes. The currency conversion is used for share prices quoted on other currencies than Euro. The free-float is round up to the next 5%. The calculation of the indices takes place every 15 seconds.

In the case of the Dutch AEX index, stocks eligible are the companies listed in Euronext Amsterdam. It is comprised of the 25 most traded companies. The weighting is based on a free-float market capitalization. The capping is 15%. The review of the composition is normally annual but quarterly replacement possible.

The eligible stocks for the BEL20 are companies listed on Euronext Brussels and that are trading continuously. The index is made up of a maximum 20 stocks having higher free-float market capitalization than the level of BEL20 index multiplied by Euro300,000. The capping is 12% and the review of the composition is annual with quarterly replacement allowed.

The eligible stocks for the CAC40 are companies listed on Euronext Paris or companies with different market reference, but fulfilling specific criteria. The selection of the index's 40 stocks is decided by the Conseil Scientifique guided by free-float adjusted market capitalization and turnover. The capping is 15% and the review of the composition takes place every quarter.

If the calculation of the index is very similar, the main difference between the indices lies in the criteria used deciding the inclusion of stocks in the index and the formal revision of the composition. Indeed, the Dutch index represents the most liquid shares, the Belgian index the higher capitalisation and the French index is in equilibrium between the two criteria.

Descriptive statistics for each index as well as preliminary univariate tests are presented in chapter five. Two returns series are created for each index price: log-returns and, using interbank as free rate excess returns. The latter series therefore represents the risk premium related to the index, hence the market premium.

Outliers are often a concern in finance research. Indeed, if one leaves the outliers in a data set, the distribution of this set might not follow a specific probability law (e.g. normal, t-distribution, or others), yielding problems for inferential analysis. However, removing outliers from the data set is the equivalent of excluding potential valuable information regarding the series. The indices' excess returns box plots (presented in appendix 2, section 10.2) show that the series include numerous outliers. The dot plots (appendix 3, section 10.3) indicate that the outliers are concentrated around specific periods (volatility clustering, see chapter five and six). This study adopts the view that the outliers include important information and therefore are not removed from the data sets.

An alternative approach could be to use dummy variables to control for the effect of outliers on the estimated models. However, the important number of outliers in the returns series makes it extremely difficult to apply this method. Moreover, none of the papers discussed in the literature (chapter 3) which use daily data use dummy variables for outliers.

The order of integration of a series is an important characteristic to determine prior to many econometric measurements. In chapter two, sections 2.3.4 and 2.3.5 review unit root tests and their problems. The main outcome is that one should apply a robust testing procedure by including a unit root test and a stationarity test, as the benefit of one test will offset the disadvantage of the other. Such an approach is adopted in chapter five by jointly using the ADF unit root test and the KPSS stationarity test.

The question of long memory in the index returns and volatility is also addressed. Section 2.3.7 of chapter two looks into the matter of long memory. Three testing procedures are mainly used in the literature: the R/S Hurst, the Whittle estimator and the GPH estimator. All three procedures are used to test the presence of long memory pattern in returns and in volatility.

4.4.2 First research objective: market efficiency

Chapter six presents the empirical work and results related to information efficiency. According to Euronext, the merger of the stock markets will result in a wider and more liquid market, an easier access to information and a decrease in transaction costs. Hence, the Euronext merger will provide the participants with a more efficient market. Thus, the main hypothesis tested in this chapter is:

H_1: The French, Belgian and Dutch stock markets are more efficient following the Euronext merger.

The review of the literature presented in chapter two shows that testing a financial market for EMH using an asset-valuation model entails a methodological issue, the joint hypothesis problem. One way to solve this problem is to analyse directly the data generating process of the series.

In theory, a market is efficient if there is no element of predictability in the data generating process. For a market to be weakly efficient, the data generating process should follow a random walk.

The method adopted in this thesis is based on the algorithms used by Hsieh (1991), Sewel et al. (1996), Al-Loughani and Chappell (1997), Panagiotidis (2005) and

Willcocks (2009). An extensive discussion of these articles is presented in chapter two, in sections 2.3.5 to 2.3.8 of the literature review and a detail description of the methodology adopted is included in chapter six.

The aim of this algorithm is to estimate a parsimonious model capturing the data generating process of each series. The procedure involves the fitting of different models, from general linear to more complex nonlinear processes. The decision criterion is that the best model should exhibit iid residuals, i.e. that there is no information left in the residuals of the model estimated. Different diagnostic tests are used, but the Brock, Dechert, Scheinkman and LeBaron (BDS) test for independence (1996), which verifies the iid of a series, is the main hurdle. The original data set is divided into three sub-periods: the pre-integration, the integration and the post-integration periods. The testable hypothesis for each sub-period is that the market follows a random walk, i.e. it is efficient. If the null is rejected, then the market follows a process that may include some elements of predictability.

4.4.3 Second research objective: market integration

Chapter seven presents the empirical work and results for the second research objective: the level of market integration between the three markets before and after the merger. Again, according to Euronext, a direct benefit to market participants from the merger is that they can invest from a wider range of equity, helping to diversify their portfolio. However, the merger may increase the integration of the equity markets. Indeed, by creating one company, with one common operating platform, the merger provides the investors with one market, Euronext, rather than three separated ones. Consequently, the investors in these markets may be subjected to the same risks. Market integration may therefore affect the real choice of investment for portfolio diversification.

Hence, the main hypothesis tested in chapter seven is:

H_2: Euronext has increased the integration of the French, Belgium and Dutch stock markets.

The outcomes of the review of literature in chapter three indicate that there are different approaches and methods to investigate financial integration. In this chapter, a direct measurement of integration is adopted: the assessment of the co-movements between markets. The econometric methods used include the cointegration analysis (a static model), and conditional correlation (a dynamic model). The combination of these two methods should allow for robust conclusions.

An alternative approach to model stock market integration could be to use panel econometrics. Panel models have the advantage of benefiting from both a time series and cross-sectional analysis. Moreover, dynamic panel techniques allow for lagged value of the dependent variable to be included in the model. In finance, panel techniques are often used when analysing jointly financial series and economic determinants for different countries (see for example Edison et al. 2002; Carrieri et al. 2007). However, this approach often implies a low time series frequency (monthly, quarterly or yearly) and a large number of cross-sectional units.

The strategy adopted in this thesis is to focus on the co-movements of the three Euronext stock markets and a control variable, the German market, using daily frequency. Furthermore, it does not seek to investigate the relationship between macroeconomics determinants and stock markets movements. Hence, in line with the literature presented in chapter 3, a multivariate time series approach is preferred.

Cointegration analysis is adopted by many researchers (for example, Masih and Masih 1997, 2004; Shamsuddin and Kim 2003; Leong and Felmigham 2003) and review of their articles is presented in section 3.5.1. In this framework, the testable hypothesis is that if stock markets are integrated, then the series studied should be cointegrated, i.e. present long-run equilibirum. If the series are cointegrated, then an error correction model, which captures the short-run correction to the long-run equilibrium, can be estimated and the short-run dependences between the series can be analysed. Most of the authors above mentioned, when examining a large sample and/or wanting to assess the impact of a specific event, divide their original sample into sub-periods. Likewise, in this study, the cointegration analysis is applied to the overall sample and to the three sub-periods: pre-integration, integration and post-integration.

The conditional correlation analysis is a more recent econometric tool but also widely used (for example, Kim et al. 2005, 2006; Bartram et al. 2007; Egert and Kocenda 2011). A review of these articles is presented in section 3.5.2. In this study, the methodology based on conditional analysis does not include a testable hypothesis per se. It is mainly a graphical analysis of the daily conditional correlation over the entire period. However, some descriptive statistics of the correlation in each sub-period are calculated.

The main econometric software used in this thesis is Eviews 7, with the exception of the long memory analysis presented in chapter 5 (the R/S Hurst, the Whittle estimator and the GPH estimator procedures) which is performed using the open-source software Gretl. Both Eviews7 and Gretl are time series software.

4.4.4 The Euro currency: a methodological issue

The two empirical research chapters include a methodological issue: the introduction of the European currency. Indeed, the three stock exchanges are in member countries of the Euro-zone. Moreover, the introduction of the Euro in the financial system on 1st January 1999 and the bringing into the circulation of Euro coins and notes on 1st January 2002, coincided with the Euronext merger. It is therefore difficult to differentiate between the impacts of Euronext integration and the introduction of the Euro currency. In order to take into account the impact of the Euro currency, the following strategies are adopted. In chapter six, which investigates the data generating process of each series, a dummy variable, with value 0 before 1st January 1999 and 1 after, is used when the series are analysed over the entire period. If the dummy variable is significant, then it indicates an impact from the introduction of the Euro.

In the multivariate analysis in chapter seven, the German main index DAX30 is introduced in the system as a control variable. The German index is chosen as it is from an economy of the Euro-zone but the stock exchange is not part of the Euronext. If the DAX30 has a different pattern than the other indices, then the results indicate an impact from the Euro introduction.

4.5 Minimising Risks Associated to Reliability and Validity

Reliability and validity are criteria to assess the credibility of the findings from the research. Reliability is concerned with the consistency of the findings while validity refers to the extent to which the findings represent what was supposed to happen. (Saunders et al. 2007, p. 149-150; Collis and Hussey 2003, p. 58-59).

The threats to validity can be categorised in two main groups: threats to internal validity, which are related to the design of the research; and threats to external validity, which concerns the generalisation of the results of the study (Ryan et al. 2002; Saunders et al. 2007, p. 150-151).

Research studies which adopt the positivist paradigm and deductive approach are generally characterised by highly structured methodologies and methods to facilitate replication. Therefore, these studies enjoy high reliability (Saunders et al. 2007, p.117-118; Collis and Hussey 2003., p. 58). As mentioned earlier, the approach of this study is deductive in nature as it involves the formulation of testable hypotheses from a theoretical framework, followed by the collection of secondary data and its analysis using appropriate econometric tests. A thorough and detailed description of the methodology and methods adopted will minimise the threat to reliability.

However, a deductive approach might suffer from low validity, as it may use inappropriate procedures or misleading data (Collis and Hussey 2003, p.59). In order to address these threats, great care has been given to the choice of the data and the procedures adopted.

Spanos (1999, p. 28-29) categorises the limitations of economic data into two categories: accuracy and nature. Arguing that no sophisticated statistical arguments can salvage bad quality data, he insists on the need for a deep understanding of the nature and the accuracy of the data. The data used in this study are official indices of the three stock markets. These indices are chosen as they are computed and disseminated in the same way throughout the period of the study. Moreover, the data are collected from Datastream which is a database with a trustworthy reputation.

An extended and critical review of the existing literature, focusing on the most recent and reputable sources, ensures the development of a sound theoretical framework. Moreover, the literature review provides a set of appropriate econometric tests, addressing the potential weaknesses of each test. Finally, following Spanos' recommendation (1999, p. 16), the theoretical model is constructed independently of the observed data.

The development of a theoretical model, the analysis of the nature and accuracy of the data and the critical assessment of the statistical procedures ensures a minimisation of the internal threats. By addressing the threats to internal validity the researcher increases the external validity (Ryan et al. 2002).

4.6 Limitations and Delimitations

Limitations are related to the potential weaknesses of the study while delimitations deal with the boundaries of the research. Both are connected to the research strategy of the study: the design, econometric tools and data used.

The integration of the Euronext is a long and gradual process, with different stages of legal and operational integration. Each market had its own needs and pace. Thus it is difficult to date it exactly. Moreover, as mentioned above, the Euro currency was introduced in the same time period as the integration. The research strategy includes strategies to address these issues: the creation of an "integration period (2000-2002)"; the use of dummy and control variables. However, it is difficult to ascertain that the results are not influenced by these events.

The stock indices used in this study are proxies for the markets researched. However, they truly represent only certain categories of the stock listed, the blue-chip shares. Using different indices, such as for example small-cap shares or even specific stocks may yield different results for the univariate and multivariate analysis.

The stock indices are also subject to the survivorship bias of each individual stock. Over the 21-year period of this study, the composition of each index has changed. It is extremely difficult to analyse each individual changes. However, because the indices calculation criteria have not been modified and the window span is large, the impact of these individual changes is extremely small.

The study uses daily frequencies. Daily data include more information than longer frequency (e.g. weekly or monthly) data, but also more noise. Hence, the data generating process of weekly or monthly data may be captured with less complex models in the univariate analysis. The multivariate analysis may also provide different results. Moreover, the econometric tests considered in this study assume the use of critical values. It is extremely difficult to be sure that the probability distributions used are representative of the true data generating processes of the series.

4.7 Summary

This chapter has presented a discussion of the main methodological issues and a brief introduction to the methods proposed.

This study adopts a positivist research study and a deductive/quantitative approach. Indeed, influenced by the outcomes of the literature review from chapter two and three, the theoretical frameworks for this study is EMH and market integration and the methodology involves testing market data using econometric tools.

Related to the econometric approach, the general-to-specific strategy starts from a very general specification and reduces it to the most parsimonious model. This strategy is closely related to the Lakatos programme which posits that a model is superior to another when it can explain the anomalies of the other and predicts more novel facts.

The research strategy, design, hypotheses, and an overview of the data econometric tools proposed in this thesis are introduced in the second part of the chapter. This study’s strategy can be qualified as quasi-experimental as it is very close to empirical research but without a direct manipulation of the independent variable. The hypotheses and the methods to test them are deduced from the outcomes of the literature review.

5 Descriptive Statistics and Univariate Analysis

5.1 Overview

This chapter presents and describes the data used in this study. First, it looks at the price levels of the national indices, the transformation to log-returns and excess returns, which are computed using a risk free proxy. Then, the order of integration of the series is determined using a robust approach, the joint confirmation procedure. Finally, a preliminary assessment of eventual persistence pattern in returns and volatility is provided applying the Rescaled Range (*R/S*) Hurst analysis and long memory tests. This preliminary univariate analysis is important to understand the nature of the data and is a prerequisite for tests presented in the following two chapters.

5.2 Sample: National Indices Prices

The sample is comprised of the daily prices of the national indices of France (CAC40), Belgium (BEL20), and the Netherlands (AEX) for the period beginning 01/01/1990 and ending 10/12/2010, which means 5465 observations. The data was retrieved from Datastream. The default currency is the Euro and the codes for the series are:

AEX: AMSTEOE
BEL20: BGBEL20
CAC40: FRCAC40

The time plot in Figure 5.1 shows that, overall, all three indices have a tendency to follow the same trend throughout the 21 year period. Indeed, the three indices had their lowest values around the same time: the same day for the BEL20 and the AEX (01/16/1991) and two days earlier for the CAC40 (01/14/1991) (table 5.1). However, during a period of approximately one year, from May 1999 to April 2000, the Dutch and French indices rallied to reach, in 09/04/2000, their maximum value for the 21 year period, whilst the Belgian index was losing value. Table 5.1 shows that the mean and the median for each index are relatively close.

Figure 5.1: National indices daily closing prices for the period 01/01/1990-11/12/2010

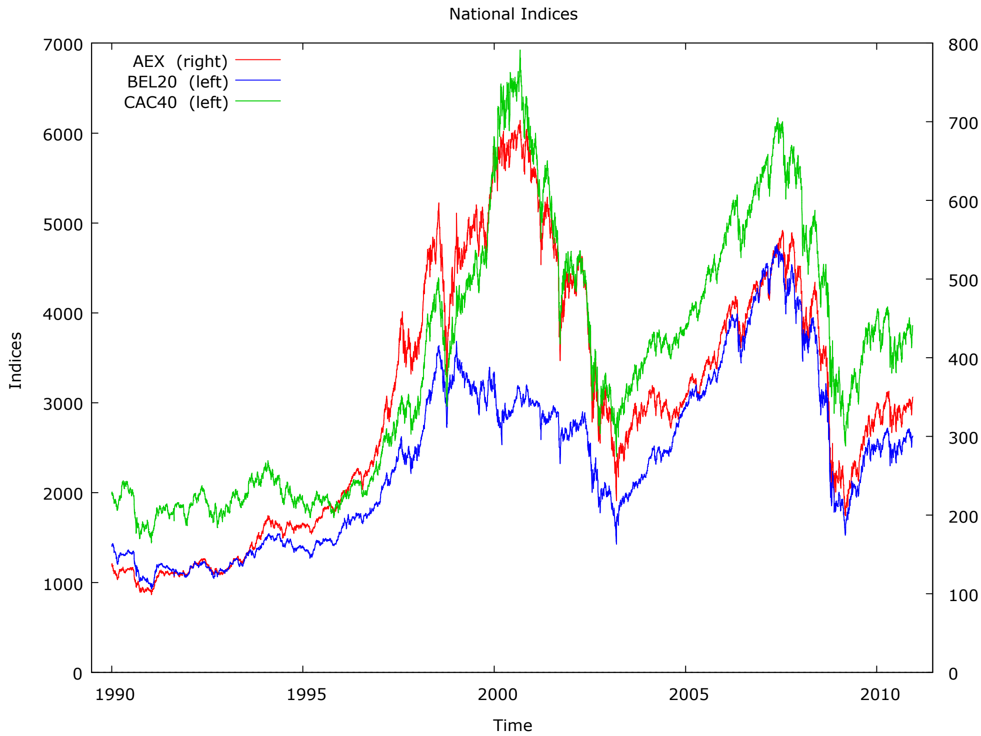


Table 5.1: National indices prices, 01/01/1990-10/12/2010, descriptive statistics

	AEX	BEL20	CAC40
Mean	345.02	2382.8	3470.7
Median	336.00	2417.0	3450.2
Minimum	98.750 (01/16/1991)	928.57 (01/16/1991)	1441.2 (01/14/1991)
Maximum	701.56 (09/04/2000)	4756.8 (05/23/2007)	6922.3 (09/04/2000)

5.3 National Indices Returns

Two types of returns are commonly used in finance: the log-returns and the excess returns. In this study, both returns are considered in order to assess whether the results from the empirical research are sensitive to the type of returns used.

The log-returns of a financial series are computed as the natural logarithm of the first difference of the prices, or levels, of this series. In this paper, the log-returns for each index are calculated as:

$$r_{it} = \ln\left(\frac{y_{it}}{y_{it-1}}\right), \tag{5.1}$$

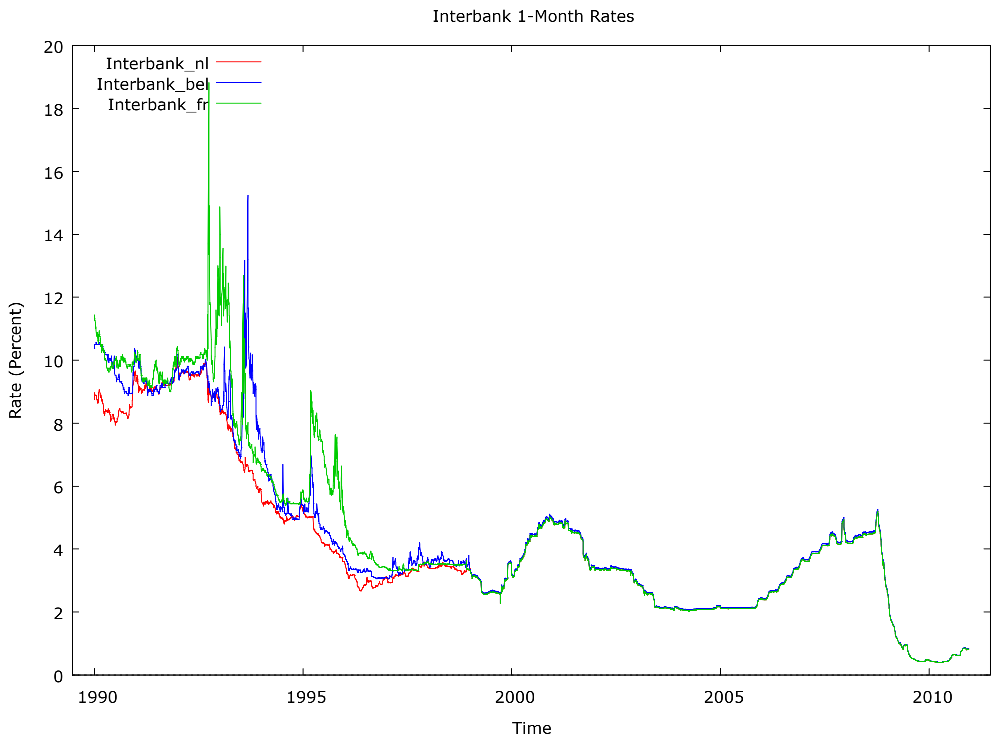
where r_{it} indicates the log-return for index i at time t, y_{it} indicates the prices of index i at time t, andy_{it-1} indicates the prices of index i with a one-day lag.

To compute the excess returns of a financial series, a proxy for the risk-free rate is deducted from the log-returns. As the prices series considered in this study are National indices, the computed excess returns are also the market risk premium for these markets.

The risk free proxies considered in this study were originally Treasury bills, with one month maturity, for each country. However, T-bill rates for the Netherlands were not available for the entire period under consideration. The next option was then the Interbank rates, also with one month maturity, for each country.

The daily Interbank rates for each country were retrieved from Datastream. The default currency is the national currency and the codes are:
Dutch Interbank, one-month: AIBOR1M
Belgian Interbank, one-month: BIBOR1M
French Interbank, one-month: PIBOR1M

Figure 5.2: Time plot for one-month Interbank rates, Netherlands, Belgium and France, 01/01/1990-10/12/2010.



The time plot in Figure 5.2 shows that each country Interbank rate fluctuated apart from the first half of the period but were identical in the second half. This is indeed because on January 1, 1999, the fixed exchange rates between the then national currencies and the Euro were officially announced. One month later, in February 1999, the Interbank rates of the three countries were the same.

The Belgian and the French Interbank rates showed two large shocks in the period 1992-1993. More specifically, the French rate increased sharply in September 1992, the period corresponding to the Exchange Rate Mechanism (ERM) crisis and the exit of the pound sterling on Wednesday 16/09/1992. It is worth noting that the ERM crisis did not affect the Belgian and Dutch rates in the same harsh manner.

The Belgian interbank rates picked in August and September 1993. This period corresponds to a harsh economic crisis for the country (1992-1993) coupled with a constitutional crisis. The constitutional crisis was temporally resolved at the end of the month of September with the introduction of the fourth State reform.

The correlation matrices presented in tables 5.2-5.4 depict the same pattern: table 5.2 shows the correlation for the entire period, table 5.3 for the period preceding the introduction of the Euro, 01/01/1990-31/01/1999 and table 5.4 for the period of the Euro, 01/02/1999-10/12/2010. During the pre-Euro period, the Dutch and Belgian Interbank rates presented the highest correlation (0.9567), followed by the Dutch and the French (0.9336) and French and Belgian rates (0.9228).

Table 5.2: Correlation matrix, Interbank rates, 01/01/1990-10/12/2010

	Interbank Netherland	**Interbank Belgium**	**Interbank France**
Interbank Netherland	1.00		
Interbank Belgium	0.979	1.00	
Interbank France	0.9659	0.9650	1.00

Observations: 5465, 5% Critical value (two-tailed) = 0.0265

Table 5.3: Correlation matrix, Interbank rates, 01/01/1990-31/01/1999

	Interbank Netherland	**Interbank Belgium**	**Interbank France**
Interbank Netherland	1.00		
Interbank Belgium	0.9567	1.00	
Interbank France	0.9336	0.9228	1.00

Observations: 2372, 5% Critical value (two-tailed) = 0.0402

Table 5.4: Correlation matrix, Interbank rates, 01/02/1999-12/10/2010

	Interbank Netherland	**Interbank Belgium**	**Interbank France**
Interbank Netherland	1.00		
Interbank Belgium	1.00	1.00	
Interbank France	1.00	1.00	1.00

Observations: 3094, 5% Critical value (two-tailed) = 0.0352

Table 5.5 presents the summary statistics for the Interbank rates. The French and the Belgian rates have the highest mean, 4.91% and 4.52% respectively, as well as the highest volatility, with coefficient of variation of 0.64 and 0.61. The Dutch rates are the most conservative with a mean of 4.17% and a coefficient of variation of 0.59. All three series are positively skewed and only the French rates present positive excessive kurtosis.

Table 5.5: Summary statistics, one-month Interbank rates, Netherland, Belgium, France, 01/01/1990-10/12/2010.

	NETHERLAND INTERBANK 1 MONTH - OFFERED RATE	BELGIUM INTERBANK 1 MONTH - OFFERED RATE	FRANCE INTERBANK 1 MONTH - OFFERED RATE
Mean	4.1682	4.4173	4.5911
Median	3.4240	3.6200	3.5605
Minimum	0.39700	0.40250	0.39700
Maximum	10.080	15.234	18.813
Standard Deviation	2.4489	2.7001	2.9271
Coef. of Variation	0.58751	0.61125	0.63757
Skewness	0.88730	0.90728	0.96229
Excessive Kurtosis	-0.012669	-0.082266	0.12894

Observations: 5465

T-Tests for difference in means, presented in table 5.6, show that the mean values of the Interbank rates were significantly different for each pair of countries. This is due to the differences in the rates during the period 1990-1998.

Table 5.6: T-tests for difference in means, Interbank rates, 01/01/1990 – 10/12/2010.

	Belgium	**France**	**Belgium**	**Netherlands**	**France**	**Netherlands**
Mean	4.4173	4.5911	4.4173	4.1682	4.5911	4.1682
Variance	7.2906	8.5679	7.2906	5.9969	8.5679	5.9969
Correlation	0.9649		0.9792		0.9659	
Df.	5464		5464		5464	
T-Statistics	-16.51		31.68		36.91	

Observations: 5465, hypothesised mean difference: 0

The Interbank rates, when retrieved from the database, are expressed as annual rates. In order to subtract them from the daily indices log-returns, they need to be converted to daily rates, using the following transformation:

$$r_{daily,i} = \left(\sqrt[260]{1 + r_{annual,i}}\right) - 1,$$

where $r_{daily,i}$ is the computed daily Interbank rate, one-month maturity, for country i and $r_{annual,i}$ is the annual Interbank rate, one-month maturity, for country i.

The reason for taking the 260th root from each annual rate is that the series include about 260 observations for one year.

Once the risk free proxies are converted to daily rates, the excess rates of return can be computed as the difference between the log-returns of each national index and the risk free for the respective country. Tables 5.7-5.9 show the summary statistics for both types of returns for each national index. The mean of the log-returns for each series is positive. However the means of the excess returns for Belgium and France are negative. Moreover, the deduction of the risk free has a very important effect on the volatility of each series: it increased the standard deviation of each series only marginally but, as would be expected, as the mean decreased, the coefficient of variation increased drastically. The most acute example is the case of the AEX, with a coefficient of variation that increased 7.8 times. The third and fourth moments of both types of returns are pretty similar: the Dutch and French returns exhibit negative skewness and all the returns for all three countries have excessive kurtosis. According to Das and Uppal (2004), “returns on international equities are characterized by jumps occurring at the same time across countries, leading to a return distribution that is fat-tailed and negatively skewed.”(p.2831)

Table 5.10 shows the results of t-tests comparing the means of the log-returns and excess returns for each national index, with a hypothesised mean difference of zero. All tests are highly significant, indicating a difference in means. The risk free proxy for each country is therefore different for the period prior the EMU, reflecting the differences in the country’s respective economic and monetary policy. More specifically, the spread between log- and excess return is more important for the French than for the Belgian and Dutch indices for the period 1990-1998.

Table 5.7: Summary statistics for log-returns and excess returns, AEX, 02/01/1990-10/12/2010

	AEX log-return	AEX excess return
Mean	0.00017232	0.000022096
Median	0.00034210	0.00016772
Minimum	-0.095903	-0.096089
Maximum	0.10028	0.10010
Standard Deviation	0.013722	0.013724
Coefficient of Variation	79.633	621.10
Skewness	-0.14736	-0.14265
Excessive Kurtosis	6.9374	6.9367

Observations: 5464

Table 5.8: Summary statistics for log-returns and excess returns, BEL20, 03/01/1990-10/12/2010

	BEL20 log-return	BEL20 excess return
Mean	0.00011502	-0.000043791
Median	0.000020544	-0.000095420
Minimum	-0.083193	-0.083376
Maximum	0.093340	0.093242
Standard Deviation	0.011484	0.011486
Coefficient of Variation	99.839	262.30
Skewness	0.045077	0.049275
Excessive Kurtosis	7.7017	7.6992

Observations: 5463

Table 5.9: Summary statistics for log-returns and excess returns, CAC40, 02/01/1990-10/12/2010

	CAC40 log-return	CAC40 excess return
Mean	0.00012011	-0.00004690
Median	0.00000	-0.00012070
Minimum	-0.094715	-0.094901
Maximum	0.10595	0.10576
Standard Deviation	0.013950	0.013952
Coefficient of Variation	116.15	312.20
Skewness	-0.0079309	-0.0056658
Excessive Kurtosis	5.0498	5.0497

Observations: 5464

Table 5.10: T-tests for difference in means, log- and excess returns, 01/01/1990 – 10/12/2010

	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
Mean	0.0001723	0.00022096	0.00011502	-.00004379	0.00012011	-0.00004690
Variance	0.0001882	0.00018834	0.00013188	0.0001319	0.00019464	0.00019469
Correlation	0.9999802		0.99996604		0.99997313	
Df.	5463		5463		5463	
T-Statistics	128.8016		123.9895		119.0447	

Observations: 5464, hypothesised mean difference: 0

An examination by eye of the indices' excess returns time plots (Figures 5.3 to 5.5) shows periods of low and high volatility, with, in certain cases, absolute daily returns in excess of 5%. Additionally, volatility clustering patterns seem to appear at approximately the same periods for each index.

Figure 5.3: Time plot for AEX excess returns, 02/01/1990-10/12/2010.

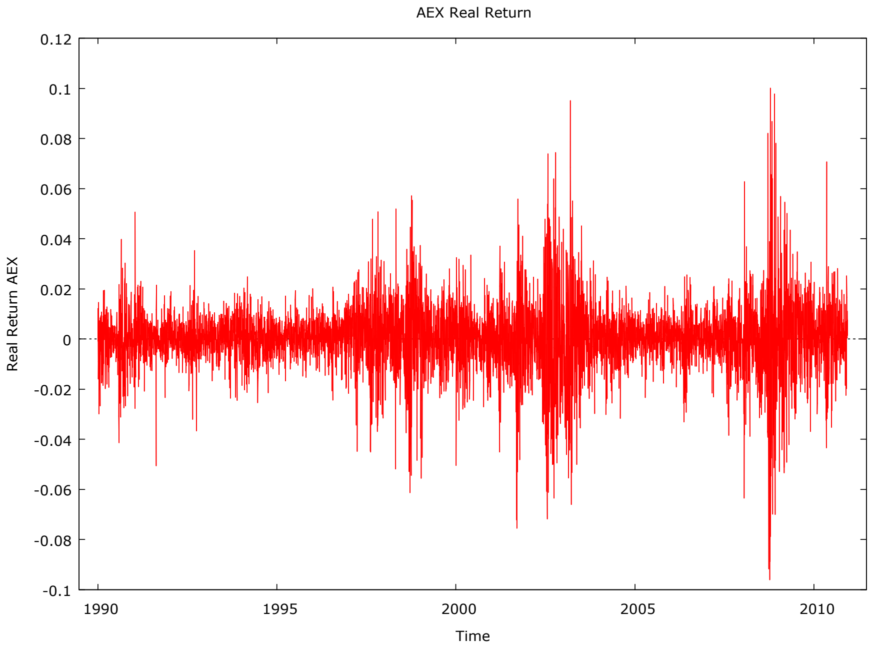


Figure 5.4: Time plot for BEL20 excess returns, 03/01/1990-10/12/2010

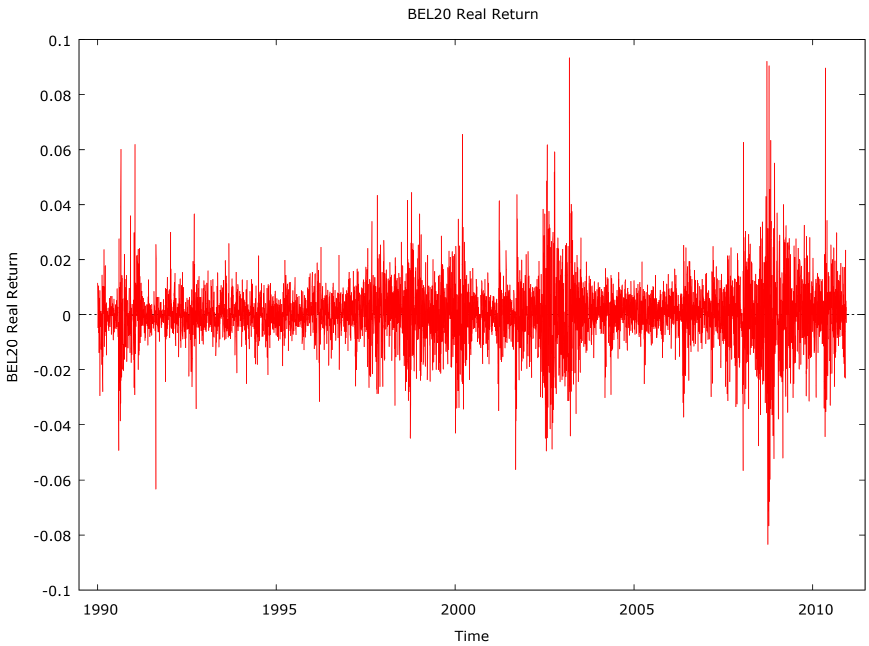


Figure 5.5: Time plot for CAC40 excess returns, 02/01/1990-10/12/2010

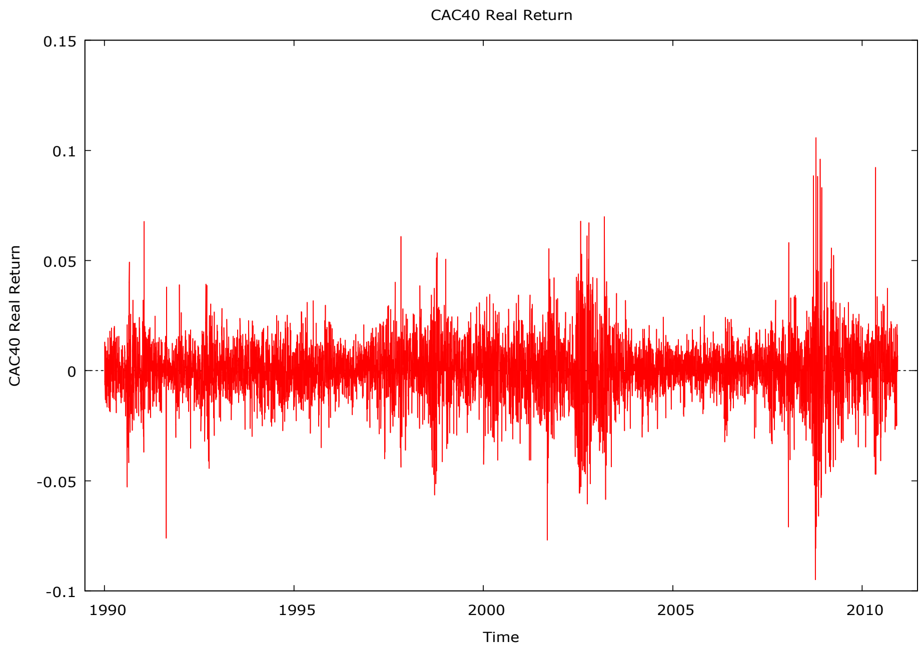


Table 5.11 and 5.12 present the correlation coefficients between the two types of indices' returns. The highest correlation is exhibited by the Dutch-French indices, followed by the Dutch-Belgian, while the Belgian-French pair is less correlated. Interestingly, the risk free impacts only marginally on the synchronous correlations between indices' returns.

Table 5.11: Correlation coefficients, excess returns, 01/01/1990 – 10/12/2010

	AEX excess return	BEL 20 excess return	CAC 40 excess return
AEX excess return	1.00		
BEL 20 excess return	0.7938	1.00	
CAC40 excess return	0.8580	0.7550	1.00

Observations: 5463, 5% critical value (two-tailed) = 0.0265

Table 5.12: Correlation Coefficients, log-returns 01/01/1990 – 10/12/2010

	AEX log-return	BEL 20 log-return	CAC 40 log-return
AEX log-return	1.00		
BEL 20 log-return	0.7938	1.00	
CAC 40 log-return	0.8579	0.7549	1.00

Observations: 5463, 5% critical value (two-tailed) = 0.0265

5.4 Stationarity

The order of integration is an important element for identifying the Data Generating Process of a series, as well as for the analysing the co-movements between series. Following the findings of the literature review, the procedure adopted in this research to determine the order of integration is the Joint Confirmation, i.e. the simultaneous use of two tests: one with unit root as null hypothesis and one with stationarity as null hypothesis. This robust procedure is designed to tackle the problems of power and size of the traditional unit root tests when applied alone. The tests are: the Augmented Dickey Fuller (Dickey Fuller 1979, 1981) unit root test (ADF) and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) stationarity test (KPSS).

5.5 The Statistical Tests

5.5.1 The Augmented Dickey Fuller (ADF) test

The ADF test is an improved procedure of the original Dickey Fuller (DF) test: the original DF test assumes that a series follows an autoregressive process of order 1; the ADF test allows the series to be an autoregressive process of higher order. The test is described below.

We start with the basic AR(1) process:

$$y_t = \rho y_{t-1} + x_t^{'}\delta + \varepsilon_t, \tag{5.2}$$

where $x_t\delta$ consists of optional exogenous regressors (a constant, a trend, or a constant and a trend).

The simple DF test is carried out by estimating the above equation, after subtracting y_{t-1} from both sides of the equations, assuming that the series follows an AR(1) process. To allow for potential higher order processes, AR(p), the ADF test includes p lagged difference terms of the dependent variable y on the right side of the equation:

$$\Delta y_t = \alpha y_{t-1} + x_t^{'}\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + u_t, \tag{5.3}$$

where $\alpha = \rho - 1$ and p is the order of the AR process.

The null and alternative hypotheses of the test are:

$H_0: \alpha = 0$

$H_1: \alpha < 0$

The statistical test is a t-ratio for α

$$t_\alpha = \hat{\alpha} \big/ (se(\hat{\alpha}))$$

5.5.2 The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test

As mentioned above, the KPSS test is the alternative procedure that tests the null hypothesis of stationarity. The KPSS is based on an analysis of the residuals from the regression of y_t on exogenous variable x_t :

$$y_t = x_t{}'\delta + u_t. \tag{5.4}$$

The LM statistic is:

$$LM = \sum_t S(t)^2 \big/ (T^2 f_0),$$

where f_0 is an estimator of the residual spectrum at frequency zero and *S(t)* is a cumulative residual function:

$$S(t) = \sum_{r=1}^{t} \widehat{u_r},$$

based on the residuals $\widehat{u_t} = y_t - x_t{}'\hat{\delta}(0)$. Under the null hypothesis, the process is stationary.

5.5.3 Critical values

As mentioned in chapter two, Charemza and Syczewska (1998), Carrion-i-Silvestre et al. (2001), and Keblowski and Welfe (2004) published critical values for the Joint Confirmation for various sample sizes. Since the sample size in this study does not match the sizes considered in the above articles, only two sets of critical values are taken into consideration: first, the values from Carrion-i-Silvestre et al. (2001, p.4) for a sample of 300 observations; and secondly, the approximations of asymptotical critical values provided by Keblowski and Welfe (2004, p. 260). These are reproduced in the tables 5.13 and 5.14.

Table 5.13: Critical values for the Joint Confirmation, sample size: 300

PJC	No constant		No trend (With constant)		With trend	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
0.99	-2.694	0.246	-3.592	0.149	-4.159	0.070
0.975	-2.357	0.339	-3.270	0.200	-3.851	0.084
0.95	-2.159	0.414	-3.100	0.238	-3.670	0.095

From: Carrion-i-Silvestre et al., 2001, p. 4. PJC: Probability of joint confirmation. KPSS estimated with Bartlett kernel.

Table 5.14: Approximations of asymptotical critical values for the Joint Confirmation

PJC	No deterministic term		With constant		With trend	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
0.99	-2.847	0.391	-3.735	0.236	-4.224	0.102
0.975	-2.502	0.558	-3.370	0.320	-3.896	0.130
0.95	-2.242	0.746	-3.100	0.420	-3.604	0.162

From: Keblowski and Welfe, 2004, p. 260. PJC: Probability of joint confirmation.

When comparing the critical values from table 5.13 and 5.14, Keblowski and Welfe's asymptotical approximations for ADF and KPSS (table 5.13) are larger in absolute values than these computed by Carrion-i-Silvestre et al. (table 5.14). Hence, the values of Keblowski and Welfe, make it harder for both tests to be significant. Besides the different sample sizes, it is possible that the discrepancies between the critical values are due to different parameterizations of the tests in the Monte-Carlo procedures.

5.5.4 Joint Confirmation tests

For the following ADF tests, the automatic lag selection is chosen to minimize the Schwarz (1978) Bayesian Information Criterion (BIC or SBC), with a maximum lag length of 10[3]. The BIC procedure is preferred over the Akaike Information Criterion (AIC) as it includes a penalty for including extra parameters. Therefore, asymptotically, the SBC procedure selects the more parsimonious model. Concerning the KPSS tests, the Bartlett window is used for the spectral estimation and the Newey-West for the automatic selection of the bandwidth. For these tests, the index prices were transformed into log-prices. Tables 5.15-5.17 present the results of the Joint Confirmation analysis for log-prices, excess returns, and log-returns.

[3] A discussion on the information criteria and model selection is presented in appendix 7, section 10.7.

Table 5.15: Joint Confirmation for national indices log-prices, 02/01/1990 – 10/12/2010.

National Indices	No constant, no trend		With constant		With constant and trend	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
AEX	0.8811	N/A	-1.5402	5.1178**	-0.9494	1.7964**
BEL20	0.5967	N/A	-1.3057	6.1440**	-1.4432	1.0327**
CAC40	0.5608	N/A	-1.4539	6.1539**	-1.6569	1.0991**

Observations: 5464. **significant at 5%, observations

Table 5.16: Joint Confirmation for national indices excess returns, 02/01/1990 – 10/12/2010

National Indices	No constant, no trend		With constant		With constant and trend	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
AEX	-35.0593**	N/A	-35.0565**	0.2026	-35.0662**	0.1086
BEL20	-68.0991**	N/A	-68.0939**	0.1152	-68.077**	0.1135
CAC40	-35.2282**	N/A	-35.2261**	0.1054	-35.2229**	0.1047

Observations: 5464. **significant at 5%

Table 5.17: Joint Confirmation for national indices log-returns, 02/01/1990 – 10/12/2010

National Indices	No constant, no trend		With constant		With constant and trend	
	ADF	KPSS	ADF	KPSS	ADF	KPSS
AEX	-35.0659**	N/A	-35.0881**	0.2788	-35.1056**	0.0973
BEL20	-68.1205**	N/A	-68.1205**	0.1377	-68.1172**	0.0971
CAC40	-35.2494**	N/A	-35.2553**	0.1275	-35.2573**	0.0883

Observations: 5464. **Significant at 5%

The results from the ADF tests are significant at 5% for the returns, but do not reject the null of a unit root for the indices' log-prices, indicating that the national indices are integrated of order 1, $I(1)$. These results are not sensitive to the choice of critical values.

The results for the KPSS tests are less straightforward and seem sensitive to the choice of critical values. If the asymptotic approximations are used (see table 5.14), then the null hypothesis of stationarity cannot be rejected at 5% for the returns, but can be rejected for the log-prices. This confirms the results from the ADF tests and points towards series integrated of order 1. But, if we use the Carrion-i-Sylvestre critical values for sample size 300 (see table 5.13), then some regressions including a constant and trend for the excess returns and log-returns appear non-stationary, contradicting the preceding results. However, the large sample size (5464 observations) allows us to follow the decisions of the asymptotic approximations, and hence to characterise the series as $I(1)$.

5.5.5 The Hurst-Mandelbrot Rescaled Range

Based on the early work of the hydrologist Hurst (1951) and developed by Mandelbrot (1972), the Rescaled Range (*R/S*) Hurst exponent is an assessment of persistence patterns or long-memory in series. If a series is white noise, with zero persistence, then the expected Hurst exponent is 0.5. The *R/S* exponent with a value significantly in excess of 0.5 indicates persistence, while a value less than 0.5 indicates anti-persistence. For large samples, the exponent is bounded by 0 and 1. Analysing returns with the *R/S* procedure is therefore an interesting complement to the Joint Confirmation. If the returns are a stationary white noise process, then the Hurst exponent should be around 0.5.

The *R/S* exponent is based on the following relationship:

$$R/S(x) = an^H, \qquad (5.5)$$

where *R/S* is the rescaled range of the variable x in samples of size n; a is a constant and the H is the *R/S* Hurst exponent.

When using returns, the rescaled-range statistic is given by:

$$\tilde{Q}_n \equiv \frac{1}{S_n}\left[\max_{1\le k\le n} \sum_{j=1}^{k}\left(r_j - \bar{r}_n\right) - \min_{1\le k\le n} \sum_{j=1}^{k}\left(r_j - \bar{r}_n\right)\right],$$

where r is the series returns, and S_n is the maximum likelihood standard deviation estimator:

$$S_n \equiv \left[\frac{1}{n}\sum_j \left(r_j - \bar{r}_n\right)^2\right]^{1/2}.$$

The original series is divided into subsamples and the rescaled range $\tilde{Q}_n$ statistic is computed for each of the sub-samples. The natural logarithms of these statistics are then plotted against the logarithms of the sample sizes of each sub-sample. The Hurst component H is estimated as the slope coefficient of the regression of the log of $\tilde{Q}_n$ statistics on the log of the sample size. In the econometrics software Gretl, the exponent is estimated using a binary sub-sample: starting with the entire data range, than with the two halves, then the four quarters, and so on.

Teverovsky et al. (1999, p. 212) considered that, while being not reliable for small sample sizes, the R/S analysis is effective for relatively large sample sizes: "…the most useful feature of the classical R/S analysis is its relative robustness under changes in the marginal distribution of the data, particularly if the marginals exhibit heavy tails with infinite variance.” (p.212). Drawbacks of the analysis include the sensitivity to the presence of short-range dependences in the variable and the lack of a distribution theory for the underlying *R/S* statistics. For these reasons, Lo (1991) proposed a modified *R/S* statistic, using a modified estimation of the standard deviation (see also Campbell et al. 1997). However, Teverovsky et al. (1999) showed that this procedure suffers from subjectivity in the choice of parameter and potential bias towards the null hypothesis of no long-range dependence (p. 225-226).

Table 5.18 presents the estimates of the slopes and related standard errors for the regressions of the $\log\tilde{Q}_n$ statistics on the log of the sample size for each series. Because the *R/S* is also an important graphical method (Teverovsky et al. p. 212), the graphs of each regression for the indices excess returns are produced in figure 5.6 -5.8 (log-returns have similar slopes, hence similar graphs).

Table 5.18: Rescaled Range (R/S) exponents for national indices returns, 02/01/1990-10/12/2010

National Indices	Slope	Standard Error	*R/S* Exponent
AEX excess returns	0.57764	0.0082505	0.577644
AEX log-returns	0.57687	0.0068161	0.576866
BEL20 excess returns	0.58338	0.017404	0.583377
BEL20 log-returns	0.58181	0.016574	0.581811
CAC40 excess returns	0.55455	0.0098326	0.554554
CAC40 log-returns	0.54950	0.0075848	0.549503

All estimates of the slopes are highly significant. An examination of the graphs by eye confirms that the line fits well all the $\log\tilde{Q}_n$statistics-log sample size coordinates for each regression. The values of the exponents are quite similar and lie within a range between 0.549 and 0.583.

The interpretation of the value of the *R/S* exponent is more difficult. If a variable is white noise, “then the range of its cumulated wandering (which forms a random walk), scaled by the standard deviation, grows as the square root of the sample size, giving an expected Hurst exponent of 0.5” (Gretl, p. 30). Persistence would be indicated by a value significantly in excess of 0.5, but there is no test to assess the significance of the exponent. However, the values from table 5.18 do not give strong indications in favour of the existence of long-memory in the national indices returns.

Moreover, these values can translate the existence of short term dependence in the return series.

Figure 5.6: Hurst R/S plots for AEX excess returns

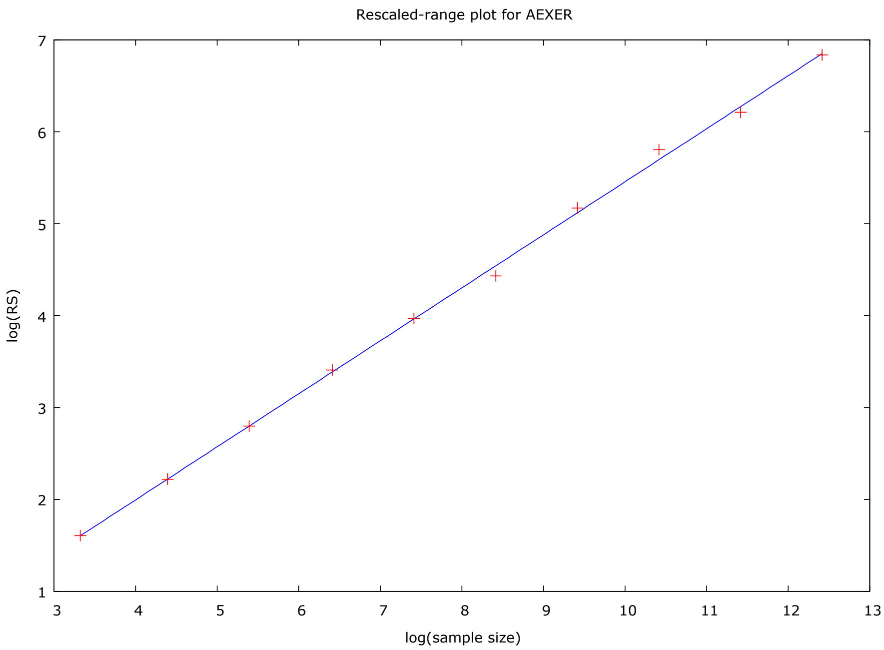


Figure 5.7: Hurst R/S plots for BEL20 excess returns

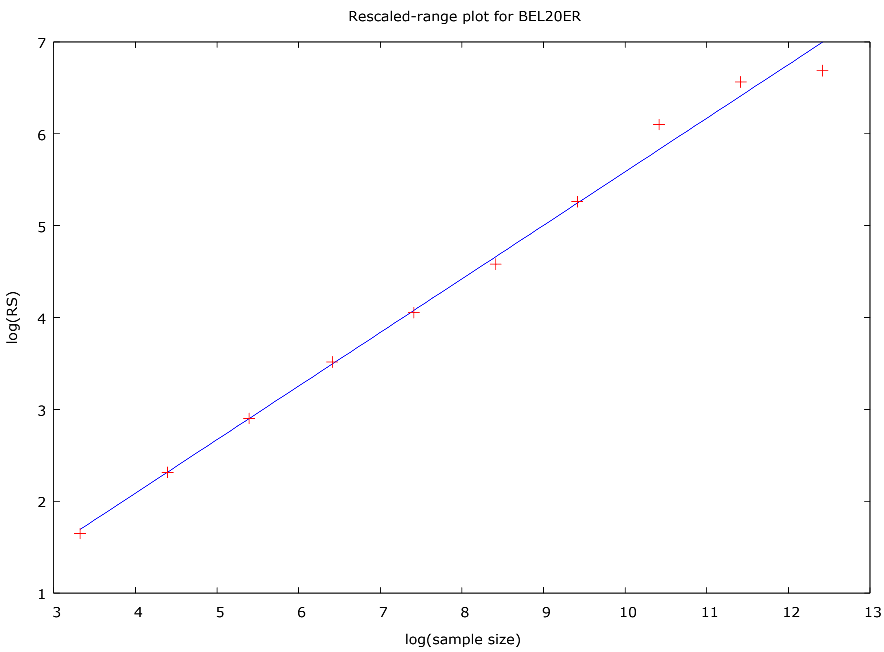
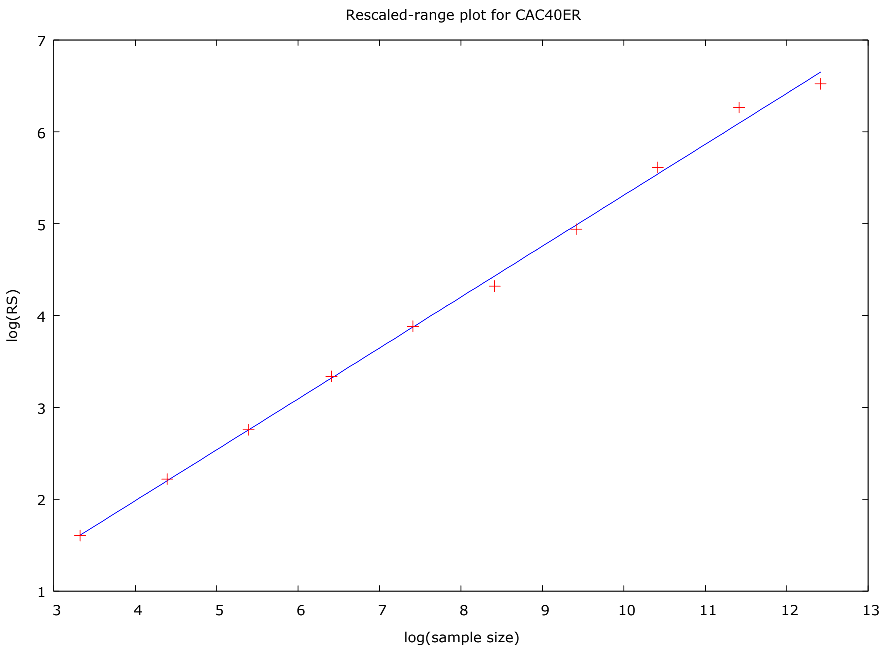


Figure 5.8: Hurst R/S plots for CAC40 excess returns



5.5.6 Fractional integration

As seen in the literature review on DGP, another procedure to test the long memory pattern of a series is to determine the order of integration of a series, assuming that the order of integration *d* is not an integer but a real number (see 2.3.7). Indeed, according to Granger and Joyeux (1980), a fractionally integrated seriesY_t can have the following form:

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t, \quad (5.6)$$

where: $\varepsilon_t \sim iid(0, \sigma^2)$, and $(1-L)^d$ is the fractional differencing operator. Hamilton (1994) explained that the scope of fractional-difference specification is to capture parsimoniously large-order ARMA processes that decay slowly.

There are different procedures to estimates the order of integration *d.* Table 5.19 shows the results of two popular techniques, the Geweke and Porter Hudak (GPH) test, (1983) and the local Whittle estimator proposed by Robinson (1995).

The interpretation of the estimates of the order of integration d is as follows:

1. if $0.5 < d < 1$, then the series is covariance nonstationary but mean reverting;
2. if $-0.5 < d < 0.5$, then the series is covariance stationary;
3. if $0 < d < 0.5$, the series is believed to exhibit persistence (i.e. the series is stationary mean reverting);
4. if $d = 0$, then the series is said to have no memory; and
5. if $0 > d > -0.5$, then it exhibits negative autocorrelation.

Table 5.19: Fractional integration, Local Whittle Estimator and GPH test for returns

National Indices	Local Whittle Estimator	p-value	GPH test	p-value
AEX excess return	0.051161 (0.0380143)	0.1784	0.120904 (0.0486569)	0.0139
AEX log-return	0.0489723 (0.0380143)	0.1977	0.116132 (0.0486632)	0.0181
BEL20 excess return	0.0488334 (0.0380143)	0.1989	0.110059 (0.0553908)	0.0485
BEL20 log-return	0.0440769 (0.0380143)	0.2463	0.103147 (0.055585)	0.0652
CAC40 excess return	0.0442334 (0.0380143)	0.2446	0.0523528 (0.048272)	0.2797
CAC40 log-return	0.0392493 (0.0380143)	0.3018	0.0432854 (0.048321)	0.3716

Lag order automatically chosen as $T^{0.6}$, i.e, 173. Standard error in parenthesis.

Table 5.19 presents the results for the indices' returns. According to the Local Whittle Estimator, the estimates for the order of integration d are not significant, hence the return series are assumed to have no memory. However, the GPH test results show that the Dutch and Belgian returns exhibit light long-memory behaviour with an estimate of d around 0.1. The estimates are more significant for the Dutch returns (5% level of significance) and less for the Belgian returns (10% level of significance).

On the other hand, the results from table 5.20 show strong evidence supporting the presence of a long memory process in the squared returns. Except for the Dutch index, all the estimates for the fractional integration parameter d are positive but smaller than 0.5, indicating a weakly stationary mean reverting process. The results the Dutch index indicate a marginal nonstationary volatility process, but as the estimated d is smaller than 1, the process is still mean reverting, i.e. "innovation will have no permanent effect on its value" (Caporale and Gil-Alana 2004b, p.350).

Table 5.20: Fractional integration, Local Whittle Estimator and GPH test, for squared returns

National Indices	Local Whittle Estimator	p-value	GPH test	p-value
AEX excess return	0.502123 (0.0380143)	0.0000	0.517661 (0.0469347)	0.0000
AEX log-return	0.502605 (0.0380143)	0.0000	0.518571 (0.0471431)	0.0000
BEL20 excess return	0.424677 (0.0380143)	0.0000	0.462664 (0.0500584)	0.0000
BEL20 log-return	0.424663 (0.0380143)	0.0000	0.462461 (0.0500827)	0.0000
CAC40 excess return	0.446311 (0.0380143)	0.0000	0.47018 (0.0508788)	0.0000
CAC40 log-return	0.446266 (0.0380143)	0.0000	0.470386 (0.0511917)	0.0000

Lag order automatically chosen as $T^{0.6}$, i.e, 173. Standard error in parenthesis.

Therefore, the results of the fractional integration analysis show weak evidence of long memory in the indices' returns series but strong evidence in the indices' squared returns. Therefore, the returns series are stationary and appear to have weak or no memory. The volatility of these returns series are weakly stationary and exhibit a mean reverting process. These results are in line with Lobato and Savin (1998), Po (2000), Assaf (2006), and Caporale and Gil-Alana (2002, 2004a).

Caporale and Gil-Alana (2004a) argue that "despite the length of the series, a standard model in first differences rather than a fractional integrated one might be appropriate for stock returns."(p.382). Moreover, Vougas (2004) argues that long memory in volatility disappear when the latter is modelled using a GARCH process.

5.6 Main Findings

The sample used in this study is comprised of daily prices for three national indices, AEX, BEL20, CAC40, for the period 01/01/1990-10/12/2010.

Two types of daily returns are computed: 1. the log-returns which are the log transformation of the series' first differences; 2. the excess returns which are the log-returns minus the one-month interbank rate, a proxy for the country's risk free rate. Both returns will be used for each index in the next chapter, an analysis of the data generating process of each series, allowing for sensitivity analysis.

The order of integration of the series is assessed using a robust procedure, the Joint Confirmation, which entails the simultaneous use of a Unit Root (ADF) and a Stationary test (KPSS). Moreover, specific critical values estimated for this procedure are used for inferential decisions. Results show that the log-price series are integrated of order 1, $I(1)$, an expected outcome for financial time series. Hence, the log-returns and excess returns series are stationary.

Finally, the eventual existence of long-memory in the returns is explored applying the *R/S* analysis and fractional integration analysis. According to the R/S procedure, the returns do not appear to include a persistence pattern, however, the values of the *R/S* exponent are slightly higher than expected if the returns were white noise stationary. These values may be caused by short term dependencies. Indeed, the time plot of the return series exhibits volatility clustering. According to the fractional integration analysis, the evidences supporting of long memory are weak for the returns but strong for the squared returns. This finding can be seen as an argument in favour of an ARMA-GARCH process to model the data generating process of the returns.

The next chapter explores in more depth the matter of dependencies as its focus is the identification of the series' data generating process.

6 The Data Generating Process

6.1 Introduction

The scope of this chapter is to research the first research objective: To test the information efficiency of the French, Belgian and Dutch exchanges before and after Euronext integration.

The strategy designed to address this objective was introduced in chapter four. It entails the use of a multistep algorithm to identify the data generating process of each series for the entire period, but also for the three sub-periods. If the Euronext integration has indeed improved the information efficiency of the markets, then this should show in their data generating processes.

This chapter is divided as follows: the next chapter analyses the research framework. Section 6.3 presents and discusses the estimates from linear models and section 6.4, the estimates from nonlinear stochastic models. Section 6.5 summarises the chapter's main findings.

6.2 Empirical Framework

6.2.1 Hypothesis and research design

As discussed in chapter four, the main hypothesis tested in this chapter is:
H_1: The French, Belgian and Dutch stock markets are more efficient following the Euronext merger.

In order to avoid the joint hypothesis problem, the information efficiency of each series is tested by analysing directly the data generating process of each series (see chapters two and four). In the literature, a common framework for identifying the DGP of a series is used by many authors: Hsieh (1991) for US stock markets, Sewel et al. (1996) for international stock indices; Al-Loughani and Chappel (1997) working on UK stock indices; Panagiotidis (2005) for the Greek stock index; and Willcocks (2009) focusing on the UK housing index. This framework is a multistep procedure which assesses the fit of a model by assessing the iid assumption for the residuals.
The procedure can be summarised as follows:
Step 1: To assess the stationarity of the series.

Step 2: To model the stationary series using an appropriate linear model and save the residuals.
Step 3: To test the residuals for the iid assumption. If the residuals are iid, then the series is assumed to be explained by the linear model of step 2.
Step 4: If residuals are not iid, then there is evidence of stochastic nonlinearity in the series. The conditional variance of the series is modelled and the residuals are saved.
Step 5: Same as step 3, to test the residuals from the model for the iid assumption. If the residuals are iid, then the DGP is explained by the model of step 4.
Step 6: If the residuals are not iid, then other models should be used: e.g. a nonlinear stochastic model (e.g. long-memory) or a nonlinear deterministic model (e.g. chaotic processes).

All authors mentioned above found that their index prices were integrated of the first order. Hence, they proceeded to step 2 using the indices' first differences (returns). In the second step, some authors (Hsieh 1991; Sewel et al. 1996) used an autoregressive model, others (Al-Loughani and Chappel 1997; Willcocks 2009) applied a random walk process to filter the linear dependences. All authors used the BDS procedure to test the iid assumption of the residuals, though sometimes in conjunction with other tests (e.g. the McLeod-Li, the Engle LM, the Tsay and the bicovariance tests in Panagiotidis 2005). All the authors found that linear processes were not sufficient to identify the DGP of their series and needed to model the conditional variance in order to explain the series. In most cases, parsimonious low level GARCH type models (e.g. GARCH (1, 1)) explained the series. Moreover, none of the five papers found strong evidence indicating the presence of long-memory or chaotic processes.

The research design of this chapter adopts a similar strategy, with however some differences. First, the diagnostic framework at each step includes: the Jarque-Bera test to assess the normality of the residuals, the portmanteau Q-statistics of the residuals to test for autocorrelation in the mean equation, the Q-statistics of the squared residuals to investigate autocorrelation in the variance, the Engle LM test to assess potential heteroskedasticity in the residuals and the BDS test to assess the iid of the residuals.
The lags structures considered for these tests are:
Portmanteau Q-statistics: 5 and 10 lags,
Engle LM: 1 and 5 lags,

BDS: Dimension 2 to 5.

The lag structure for the Q-test covers next week (5 lags) and two weeks periods (10 lags). The lag structures for the Engle LM and BDS test correspond to the next day and next week.

Second, if an ARMA-GARCH process needs to be estimated, then the mean and the variance are estimated jointly using the maximum likelihood estimator.

The next section looks therefore at the linear processes. If the diagnostic tests indicate that these models fail to capture the data generating process, then nonlinear processes are estimated.

6.3 Linear Models

In the previous chapter, the order of integration of the data was investigated and the price series were found to have a unit root and to be integrated of order 1. The testing procedure was the robust Joint Confirmation (joint use of unit root and stationarity tests). No specific structure was assumed about the series and the Joint Confirmation was applied to three models: pure random walk, random walk with drift and random walk with a drift and a trend.

In this chapter, we will research the data generating process using the returns series. Two types of returns are used for each series: log-difference and excess returns. Two broad families of linear models are considered: first the random walk family, then the more general class of autoregressive models.

6.3.1 Random walk processes

In this section, the $\phi_3 - \phi_1 - \hat{\tau}$ testing procedure is applied. This procedure allows for a clear choice of random walk process: i.e. a pure random walk, random walk with drift, or random walk with drift a trend.

6.3.1.1 Background

A pure random walk is given by the following equation:

$$y_t = \phi_1 y_{t-1} + \varepsilon_t, \tag{6.1}$$

where y_t is the price level of a series and $\phi_1 = 1$.

If we take the first differences, we have:

$$\Delta y_t = \varepsilon_t, \tag{6.2}$$

where ε_t is a white noise process. This implies that the return of series y follows a white noise process, leaving no evidence of predictability for investors. This is the reason why the random walk process is associated with efficiency of the market.

A random walk process can also include drift:

$$y_t = \mu + \phi_1 y_{t-1} + \varepsilon_t, \tag{6.3}$$

where μ is drift (constant) and $\phi_1 = 1$.

The return (first difference) is given by:

$$\Delta y_t = \mu + \varepsilon_t, \tag{6.4}$$

where the drift is the unconditional mean of the return series.

Finally, a random walk process can also include drift and a deterministic trend:

$$y_t = \mu + \phi_1 y_{t-1} + \beta t + \varepsilon_t\,, \tag{6.5}$$

where $\beta_t$is the deterministic trend and $\phi_1 = 1$.

The return (first difference) is given by:

$$\Delta y_t = \mu + \beta t + \varepsilon_t, \tag{6.6}$$

indicating that the returns include an unconditional mean and a time trend.

In the equation 6.1, 6.3 and 6.5, the condition $\phi_1 = 1$ is essential for a random walk. If $\phi_1$is smaller but close to the value 1, then the process is qualified as a near random walk. However, if $\phi_1 > 1$ then the process is said to be explosive.

6.3.1.2 Testing framework

In order to choose the appropriate type of random walk, we use a procedure based on the Augmented Dickey Fuller test (for details, see Patterson 2000, chapter 6) and run three maintained regressions, corresponding to the above three situations.

The first maintained regression is:

$$\Delta y_t = \mu + \gamma y_{t-1} + \beta t + \varepsilon_t, \tag{6.7}$$

where $\Delta y_t$is the first difference series (returns), μ is a constant/drift, $\gamma = \phi_1 - 1$ and βt is a deterministic trend component.

The null hypotheses tested are:

$\hat{\tau}_\beta, H_0: \gamma = 0, H_1: \gamma < 0$;

$\Phi_3, H_0: \gamma = 0, \beta = 0, H_1: \gamma \neq 0$ and/or $\beta \neq 0$

If null of Φ_3 is rejected, then $\hat{\tau}_\beta$ is applied. If the null of $\hat{\tau}_\beta$ cannot be rejected, then the series has a unit root. If the null is rejected, then the series is stationary, following a random walk.

If the null of Φ_3 cannot be rejected, then the second maintained regression is run:

$$\Delta y_t = \mu + \gamma y_{t-1} + \varepsilon_t. \tag{6.8}$$

The hypotheses tested are:

$\hat{\tau}_\mu, H_0: \gamma = 0, H_1: \gamma < 0$;

$\phi_1, H_0: \mu = 0, \gamma = 0, H_1: \mu \neq 0$ and/or $\gamma \neq 0$

If the null of $\phi_1$is rejected, then $\hat{\tau}_\mu$ is tested. If $\hat{\tau}_\mu$ is not rejected, the series has a unit root. If the null is rejected, the series is stationary.

If the null of $\phi_1$cannot be rejected, then a final maintained regression is run:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t. \tag{6.9}$$

The single hypothesis tested is:

$\hat{\tau}, H_0: \gamma = 0, H_1: \gamma < 0.$

If the null cannot be rejected, then the series has a unit root. If the null is rejected, then the series is a stationary.

The critical values for the F- and T-tests in the above framework are specific and computed via Monte-Carlo simulations. They can be found in Patterson (2000) from which selected critical values are reproduced in tables 6.1, 6.4 and 6.7 below.

6.3.1.3 Random walk models estimates

$\phi_3$tests

As in the previous chapter, when using the ADF tests, the automatic lag selection is chosen to minimize the Schwarz (1978) Bayesian Information Criterion (BIC), with a maximum lag length of 10. Two regressions are run: the restricted model, assuming the null hypothesis: $\gamma = \beta = 0$, and the unrestricted model with $\mu \neq 0, \gamma \neq 0$ (the maintained $\phi_3$regression).

The computed F-statistic is given by:

$\phi_3 = \left[\left((RRSS - URSS)/URSS\right)(T^* - 3)/2\right]$,

where $T^* = T - 1$.

These computed statistics are then compared with specific critical values for the $\phi_3$test (two-sided) using a data generating process of random walk with drift (table 6.1).

Table 6.1: Critical values for $\phi_3$test

	Critical values		
Sample Size T	1%	5%	10%
200	8.542	6.397	5.433
500	8.326	6.238	5.321
1,000	8.328	6.209	5.309
5,000	8.209	6.218	5.349

Source: Patterson (2000, p. 234), tabulated from 25,000 replication with DGP $\Delta Y_t = \mu + \varepsilon_t$

From tables 6.2 and 6.3, we can see that, at the 5% level of significance, all computed values from the F-tests do not exceed the two sided critical values. The null hypothesis of the ϕ_3 tests is therefore not rejected and the next step is to consider the ϕ_1 test.

Table 6.2: Results from $\phi_3$tests on the national indices log-price series

National indices	Sample (date)	Sample size	Test Statistics
AEX log-price	01/01/1990-10/12/2010	5465	0.058941
	01/01/1990-31/08/2000	2784	5.613404*
	01/09/2000-30/10/2002	564	2.771464
	01/11/2002-10/12/2010	2116	0.049038
BEL20 log-price	02/01/1990-10/12/2010	5464	0.301687
	02/01/1990-31/08/2000	2783	5.304369
	01/09/2000-30/10/2002	564	2.563641
	01/11/2002-10/12/2010	2116	0.59173
CAC40 log-price	01/01/1990-10/12/2010	5465	0.424066
	01/01/1990-31/08/2000	2784	2.75214
	01/09/2000-30/10/2002	564	3.535508
	01/11/2002-10/12/2010	2116	0.156895

*indicate significance at 10%, ** indicate significance at 5%, ***indicate significance at 1%

Table 6.3: Results from $\phi_3$tests on the national indices return series

National indices	Sample (date)	Sample size	Test Statistics
AEX log return	02/01/1990-10/12/2010	5464	-0.79505
	02/01/1990-31/08/2000	2783	1.13621
	01/09/2000-30/10/2002	564	0.110685
	01/11/2002-10/12/2010	2116	0.040499
AEX excess return	02/01/1990-10/12/2010	5464	0.372047
	02/01/1990-31/08/2000	2783	1.762452
	01/09/2000-30/10/2002	564	0.098531
	01/11/2002-10/12/2010	2116	0.031961
BEL20 log-return	03/01/1990-10/12/2010	5463	0.110643
	02/01/1990-31/08/2000	2782	0.793379
	01/09/2000-30/10/2002	564	0.315349
	01/11/2002-10/12/2010	2116	0.73994
BEL20 excess return	03/01/1990-10/12/2010	5463	0.00
	02/01/1990-31/08/2000	2782	1.433267
	01/09/2000-30/10/2002	564	0.289053
	01/11/2002-10/12/2010	2116	0.696888
CAC40 log-return	02/01/1990-10/12/2010	5464	0.152704
	02/01/1990-31/08/2000	2783	2.009781
	01/09/2000-30/10/2002	564	0.038415
	01/11/2002-10/12/2010	2116	0.346159
CAC40 excess return	02/01/1990-10/12/2010	5464	0.002588
	02/01/1990-31/08/2000	2783	2.856633
	01/09/2000-30/10/2002	564	0.029877
	01/11/2002-10/12/2010	2116	0.317979

*significance at 10%, **significance at 5%, ***significance at 1%

ϕ_1 tests

The ϕ_1 test assesses whether the DGP can be modelled with a random walk with drift. Two regressions are run: first, a restricted model, nesting the null hypothesis: $\gamma = \mu = 0$; secondly, an unrestricted model (the maintained $\phi_1$regression): $\gamma \neq 0$ or $\mu \neq 0$.

The computed ϕ_1 statistic is given by: F=$\left[\left((RRSS - URSS)/URSS\right)(T^{*} - 2)/2\right]$.

These computed statistics are then compared with specific critical values for the $\phi_1$test (two-sided) using a data generating process of a pure random walk (table 6.4).

Table 6.4: Critical values for $\phi_1$test

	Critical values		
Sample Size T	1%	5%	10%
200	6.730	4.696	3.835
500	6.387	4.646	3.803
1,000	6.370	4.620	3.787
5,000	6.365	4.596	3.797

Source: Patterson (2000, p. 231), tabulated from 25,000 replication with DGP $\Delta Y_t = \varepsilon_t$

Table 6.5: Results from ϕ_1 tests on the national indices log-price series

National indices	Sample (date)	Sample size	Test Statistics
AEX log-price	01/01/1990-10/12/2010	5465	1.328827
	01/01/1990-31/08/2000	2784	0.094906
	01/09/2000-30/10/2002	564	0.170088
	01/11/2002-10/12/2010	2116	1.200302
BEL20 log-price	02/01/1990-10/12/2010	5463	0.897325
	02/01/1990-31/08/2000	2783	0.00
	01/09/2000-30/10/2002	564	0.218051
	01/11/2002-10/12/2010	2116	1.017888
CAC40 log-price	01/01/1990-10/12/2010	5464	1.102399
	01/01/1990-31/08/2000	2784	0.451002
	01/09/2000-30/10/2002	564	0.261898
	01/11/2002-10/12/2010	2116	1.468034

*significance at 10%, **significance at 5%, ***significance at 1%

Table 6.6: Results from ϕ_1 tests on the national indices return series

National indices	Sample (date)	Sample size	Test Statistics
AEX log-return	02/01/1990-10/12/2010	5464	0.527454
	02/01/1990-31/08/2000	2783	3.781397
	01/09/2000-30/10/2002	564	1.283175
	01/11/2002-10/12/2010	2116	0.00
AEX excess return	02/01/1990-10/12/2010	5464	0.010707
	02/01/1990-31/08/2000	2783	1.652363
	01/09/2000-30/10/2002	564	1.590791
	01/11/2002-10/12/2010	2116	0.029829
BEL20 log-return	03/01/1990-10/12/2010	5463	0.225133
	02/01/1990-31/08/2000	2782	1.011869
	01/09/2000-30/10/2002	564	0.755987
	01/11/2002-10/12/2010	2116	0.102381
BEL20 excess return	03/01/1990-10/12/2010	5463	0.038144
	02/01/1990-31/08/2000	2782	0.065058
	01/09/2000-30/10/2002	564	1.050021
	01/11/2002-10/12/2010	2116	0.01137
CAC40 log-return	02/01/1990-10/12/2010	5464	0.261442
	02/01/1990-31/08/2000	2783	1.612974
	01/09/2000-30/10/2002	564	1.536394
	01/11/2002-10/12/2010	2116	0.051439
CAC40 excess return	02/01/1990-10/12/2010	5464	0.031053
	02/01/1990-31/08/2000	2783	0.366528
	01/09/2000-30/10/2002	564	1.883467
	01/11/2002-10/12/2010	2116	0.00

*significance at 10%, **significance at 5%, ***significance at 1%

The results from the $\phi_1$tests (table 6.5 and 6.6) show that the joint null hypothesis of non-stationarity ($\gamma = 0$) and no drift ($\mu = 0$) cannot be rejected at all significance levels. The $\phi_3 - \phi_1$ testing procedure therefore indicates no deterministic trend and no drift in the GDP of the log price series and return series, for all samples. Formally, the testing procedure includes a last step, the $\hat{\tau}$ test, to ascertain the stationarity of the series. In the previous chapter, we have already established that the log price series are integrated of the order 1, using a robust approach. However, for the sake of completeness, we quickly present this last test and the appropriate critical values. The computed t-test values are already presented in the previous chapter, hence only the final outcomes are presented.

$\hat{\tau}$ tests

The ϕ_3 and ϕ_1 tests are two sided tests. To increase its power, the $\hat{\tau}$ test is one-sided, with a null hypothesis of $\gamma = 0$ (or $\phi_1 = 1$, implying non-stationarity) against an alternative hypothesis of $\gamma < 0$ (or $\phi_1 < 1$, implying stationarity). Because of its alternative hypothesis, the critical values are negative (table 6.7).

Table 6.7: Critical values for $\hat{\tau}$ test

	Critical values		
Sample Size T	1%	5%	10%
200	-2.581	-1.938	-1.619
500	-2.536	-1.943	-1.610
1,000	-2.593	-1.961	-1.624
5,000	-2.558	-1.952	-1.624

Source: Patterson (2000, p. 229), tabulated from 25,000 replication with DGP $\Delta Y_t = \varepsilon_t$

All the computed t-values reported in the previous chapter (see chapter 5) are greater than the above critical values for the log prices series and much lower for the return series.

6.3.1.4 Findings from the random walk models (ADF $\phi_3 - \phi_1 - \hat{\tau}$)

The results of the $\phi_3 - \phi_1 - \hat{\tau}$ indicate that, at the 5% level of significance and for all sample windows considered, the DGP of the log prices series have a unit root and do not present a time tend or drift.

The results of the BDS tests for pure random walk DGP are presented in appendix 4 (see section 10.4) The results strongly reject the null hypothesis of iid at 1% significance. Hence, further investigations of the DGP are necessary.

6.3.2 Autoregressive Moving Average (ARMA) Model

In this section, a more generic family of linear models, the class of autoregressive moving average models, is considered.

6.3.2.1 Background

An Autoregressive Moving Average (ARMA) model attempts to capture the linear dependencies existing in a time series using lag values of the variables and lags of the residuals.

The generic model ARMA (p, q) is given by:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-1} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-1}. \qquad (6.10)$$

If the coefficients $\phi_i = 0$, then the process collapses to a simple autoregressive (AR) model. If the coefficients $\theta_i = 0$, then the process collapses to a moving average (MA) model.

6.3.2.2 ARMA models estimates

Table 6.8 to 6.11 present estimates of ARMA process using the Ordinary Least Square (OLS) estimator for the entire period and each sub-period. The orders of the processes were determined using correlograms to identify the significant lags and minimizing the SBC criterion.

Table 6.8: Estimation of ARMA models for the entire period.

	AEX log-return	**AEX excess return**
Constant	0.000172 (0.97530)	0.0000219 (0.000174)
MA(3rd lag)	-0.059397 (0.013507)***	-0.059125 (0.013508)***
p-value Q statistics residuals (5 lags)	0.000	0.000
p-value Q statistics residuals (10 lags)	0.000	0.000
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	BEL20 log-return	**BEL20 excess return**
Constant	0.000113 (0.000169)	-0.0000461 (0.000169)
AR(1st lag)	0.081242 (0.013487)***	0.081624 ((0.013487)***
p-value Q statistics residuals (5 lags)	0.000	0.000
p-value Q statistics residuals (10 lags)	0.000	0.000
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	CAC40 log-return	**CAC40 excess return**
Constant	0.000120 (0.000178)	-0.0000448 (0.000178)
AR(1st lag)	-0.055539 (0.013510)***	-0.055209 (0.013511)***
p-value Q statistics residuals (5 lags)	0.000	0.000
p-value Q statistics residuals (10 lags)	0.000	0.000
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000

Standard error in parenthesis. *significance at 10%, **significance at 5%, ***significance at 1%

Table 6.9: Estimation of ARMA models for the pre-integration period.

	AEX log-return	**AEX excess return**
Constant	0.000582 (0.000194)***	0.000384 (0.000195)**
MA(3^{rd} lag)	-0.046384 (0.018948)**	-0.045677 (0.018948)**
p-value Q statistics residuals (5 lags)	0.166	0.167
p-value Q statistics residuals (10 lags)	0.000	0.000
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	BEL20 log-return	**BEL20 excess return**
Constant	0.000284 (0.000199)	-0.0000711 (0.000200)
AR(1st lag)	0.125820 (0.018813)***	0.126383 (0.018812)***
p-value Q statistics residuals (5 lags)	0.056	0.059
p-value Q statistics residuals (10 lags)	0.002	0.002
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	CAC40 log-return	**CAC40 excess return**
Constant	0.000430 (0.000241)*	-0.000204 (0.000241)
MA (1st lag)	-0.045863 (0.018943)**	-0.046431 (0.018942)**
p-value Q statistics residuals (5 lags)	0.066	0.071
p-value Q statistics residuals (10 lags)	0.004	0.004
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000

Standard error in parenthesis. *significance at 10%, **significance at 5%, ***significance at 1%

Table 6.10: Estimation of ARMA models for the integration period.

	AEX log-return	**AEX excess return**
Constant	-0.001287(0.000716)*	-0.001434 (0.000716)**
MA(5^{th} lag)	-0.112636 (0.042415)***	-0.112641 (0.042415)***
p-value Q statistics residuals (5 lags)	0.367	0.367
p-value Q statistics residuals (10 lags)	0.038	0.000
p-value Q statistics squared residuals (5 lags)	0.000	0.038
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	BEL20 log-return	**BEL20 excess return**
Constant	-0.000831 (0.000674)	-0.000979 (0.000674)
AR(1st lag)	0.138058 (0.041820)***	0.138014 ((0.041821)***
p-value Q statistics residuals (5 lags)	0.037	0.036
p-value Q statistics residuals (10 lags)	0.005	0.005
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	CAC40 log-return	**CAC40 excess return**
Constant	-0.001372 (0.000696)**	-0.001518 (0.000696)**
MA(5th lag)	-0.113580 (0.042496)***	-0.113563 (0.042497)***
p-value Q statistics residuals (5 lags)	0.444	0.444
p-value Q statistics residuals (10 lags)	0.104	0.104
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.098	0.099
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000

Standard error in parenthesis. *significance at 10%, **significance at 5%, ***significance at 1%

Table 6.11: Estimation of ARMA models for the period post-integration period.

	AEX log-return	AEX excess return
Constant	-0.00000853 (0.000309)	-0.0000805 (0.000309)
MA(3rd lag)	-0.070454 (0.021696)***	-0.069986 (0.021697)***
p-value Q statistics residuals (5 lags)	0.001	0.001
p-value Q statistics residuals (10 lags)	0.001	0.001
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	BEL20 log-return	**BEL20 excess return**
Constant	0.000135 (0.000274)	0.0000445 (0.000274)
MA(3rd lag)	-0.050367 (0.021722)**	-0.049722 (0.021723)**
p-value Q statistics residuals (5 lags)	0.151	0.142
p-value Q statistics residuals (10 lags)	0.019	0.019
p-value Q statistics squared residuals (5 lags)	0.020	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000
	CAC40 log-return	**CAC40 excess return**
Constant	0.0000904 (0.000249)	0.00000139 (0.000251)
AR(1st lag)	0.668653 (0.113168)***	0.661535 (0.116555)***
MA(1st lag)	-0.740029 (0.102341)***	-0.732809 (0.105736)***
p-value Q statistics residuals (5 lags)	0.001	0.001
p-value Q statistics residuals (10 lags)	0.000	0.000
p-value Q statistics squared residuals (5 lags)	0.000	0.000
p-value Q statistics squared residuals (10 lags)	0.000	0.000
p-value Engle's LM test (1 lag)	0.000	0.000
p-value Engle's LM test (5 lags)	0.000	0.000
p-value Jarque-Bera	0.000	0.000

Standard error in parenthesis. *significance at 10%, **significance at 5%, ***significance at 1%

6.3.2.3 Discussion

The autoregressive structures of each return series seem to change through time. During the first sub-period, pre-integration, parsimonious short lag term processes are fitted (except for the AEX return series), while for the next sub-period, longer lag term processes are preferred (except for BEL20 return series). It is worth noting that the SBC information criterion indicates similar processes for log-returns and excess returns of each national index.

The Q-statistics of the residuals indicate that overall autocorrelation remains present in the series after estimation of the models, with the exception of the integration period (2000-2002), where autocorrelation disappear at lower lags (5). The Q-statistics of squared residuals of the fitted processes indicate the presence of autocorrelation in the return series variance. Moreover, the results of the Engle's LM ARCH tests points to the presence of ARCH effects in the residuals of all the ARMA processes. Finally, the results for the BDS tests are presented in appendix 5 (see section 10.5). The null hypothesis of iid is rejected for all estimated processes at 1% for dimension 2 to 5.

These findings suggest that the return series cannot be explained satisfactorily with linear processes. This corroborates the plots of the return series (see chapter 5) which indicated the presence of volatility clustering. A popular approach to capture both the linear dependences and the conditional volatilities of a return series is to use ARMA-GARCH processes. Moreover, the results from the fractional analysis presented in chapter 5 showed that the return series did not exhibit long-memory, but that the squared returns did. Caporale and Gil-Alana (2004a) argued that a standard ARMA model is appropriate to model the mean equation and Vougas (2004) suggested that a GARCH process can capture the long memory in volatility.

6.4 Autoregressive Conditional Heteroskedastic (ARCH) model

The autoregressive conditional heteroskedastic (ARCH) model was first introduced by Engle (1982) in order to capture the changes in volatility that time series sometimes exhibit. An ARCH process estimates conditional variance in terms of a constant and past squared residuals of a mean equation, often estimated using a linear process.

An ARCH(p) model is given by:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-1} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-1} + \varepsilon_t, \tag{6.11}$$

$$\varepsilon_t = \sigma_t z_t. \tag{6.12}$$

$$\sigma_t^2 = \alpha_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \cdots + a_p \varepsilon_{t-p}^2, \tag{6.13}$$

where $z_t \ \sim N(0,1) i.i.d.$ are the standardised residuals,
σ_t^2 is the conditional variance at time *t*, and
ε_{t-p}^2 is the residual of the mean equation at lag p.

Equation 6.11 represents the mean equation, estimated here with an ARMA process. Equation 6.12 shows how the innovations of the mean equation are defined as function of the conditional standard deviation, σ_t and an error term, the standardized errors z_t, which are assumed to be normally and iid distributed. Finally, equation 6.13

represents the conditional variance which is expressed as a function of a constant term and past squared residuals of the mean equation.

In order to avoid the need for a high order ARCH model, Bollerslev (1986) proposed the generalized autoregressive condition heteroscedastic (GARCH) model. Essentially, he added lagged conditional variance terms to the process of past squared residuals. A GARCH *(p,q)* model is given by*:*

$$\varepsilon_t = \sigma_t z_t$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q}(a_i \varepsilon_{t-i}^2) + \sum_{j=1}^{p}(b_j \sigma_{t-j}^2), \qquad (6.14)$$

$$z_t \sim N(0,1) i.i.d.$$

Equation 6.14 represents the conditional variance as a function of lag values of the squared residuals (innovation) of the mean equation, the ARCH part of the conditional variance, and lag values of the conditional variance, the GARCH element. Low order for lag length in equation 6.14 seems to fit most financial time series (see Bollerslev et al., 1992, p. 21-22).

In a classic GARCH process, the ARCH element, the coefficient $a_i$in equation 6.14, can be interpreted as the impact of "recent news" on the conditional variance and the GARCH element, the coefficient b_j in equation 6.14, as the impact of "old news" (see Floros and Vougas 2006; Floros 2007; Filis et al. 2011). The sum of these coefficients has to be positive, but less than one for the variance process to be not explosive. In practice the sum of the coefficients is close to unity, indicating persistence of the shocks in the conditional variance.

The sources of the presence of ARCH effects in financial time series are not always clear. According to Bollerslev et al. (1992), the correlation in the conditional variances of financial time series is due to the presence of a serially correlated news arrival process: "…the notion of time deformation in which economic and calendar time proceed at different speed" (p. 21). Moreover, the market mechanisms may induce different temporal dependence in stock volatility: "…a particular automated trade execution system inducing a very high degree of persistence in the variance process" (p. 21).

Xekalaki and Degiannakis (2010) presented three main factors affecting ARCH effects in finance. The first factor is the leverage effect which states that volatility increases in response to bad news and decreases in response to good news, i.e. returns are negatively correlated to changes in volatility. Hence the presence of a leverage effect results in different impact from positive and negative shocks. This asymmetric impact can be captured by models from the family of asymmetric GARCH (e.g. Exponential GARCH, GARCH with Threshold). The second factor is the non-trading period effect which reflects "the accumulation of information during non-trading periods, as reflected in the prices when the markets reopen following a close" (p.15). The return variance after weekends or holidays is higher than on other days but is not proportional to the market close duration, i.e. it is not as high as it would be under a constant news arrival rate (Baillie and Bollerslev 1989 cited in Xekalaki and Degiannakis 2010, p. 15). The third factor, the non-synchronous effect which reflects the fact that prices are "recorded at time intervals of one length when in fact they were recorded at time intervals of another, not necessarily regular, length" (p. 16). For example, closing prices of a security are typically the prices of the last transactions, which is not the same time for all securities. The non-synchronous effect can induce auto-correlation in high-frequency index return series. The non-trading and non-synchronous effects are the consequences of the market mechanisms put forward by Bollerselv et al. (1992).

In this chapter, we consider seven models for conditional volatility: the simple GARCH model, presented above, a GARCH in Mean (GARCH-M), a GARCH with Threshold (TARCH), a GARCH in Mean with Threshold (TARCH-M), an Exponential GARCH (EGARCH), a Component GARCH (CGARCH) and a Component GARCH with Threshold (AGARCH) model. The exponential GARCH, the GARCH and component GARCH with a threshold process belong to the family of asymmetric GARCH which allow for different treatment of positive and negative shocks, hence recognizing the leverage effect.

The GARCH in mean (GARCH-M) model:

The GARCH in mean model integrates the conditional variance in the mean equation. It therefore incorporates the financial theoretical axiom stating that the investor's expected return is positively related to the risk. The mean equation is now given by:

$$y_t = \mu + c\sigma_t^2 + \varepsilon_t, \tag{6.15}$$

where y_t is an asset return series and μ and c are constants. The parameter c is the risk premium. If the value of c is positive, then the return of the asset is positively related to its volatility (Tsay, 2005, p. 123). Equations 6.12 and 6.13 remain the same.

The Threshold GARCH (TARCH/GJR) model:

A TARCH (*p, q*) model, also called GJR GARCH (Glosten *et al.*, 1993) is based on the original GARCH (*p,q*), but the conditional variance equation is now expressed as:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q}(a_i + \gamma_i N_{t-i})\,\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\left(b_j\sigma_{t-j}^2\right), \tag{6.16}$$

where N_{t-i} is an indicator for negative lag innovation, ε_{t-i}^2,

$$N_{t-i} = \begin{matrix} 1 \text{ if } \varepsilon_{t-i} < 0 \\ 0 \text{ if } \varepsilon_{t-i} > 0 \end{matrix}$$

and a_i, γ_i *and* $b_i$are non-negative parameters. For positive ε_{t-i}, the impact of the squared residuals on the conditional variance is $a_i\varepsilon_{t-i}^2$ and for negative ε_{t-i}, the contribution of the squared residuals on the conditional variance is larger: $(a_i + \gamma_i)\varepsilon_{t-i}^2$. The essence is therefore to separate the impact of positive and negative past innovation, giving a larger weight to the negative shocks. If $\gamma_i > 0$, then bad news increases volatility, which is called the leverage effect. Finally, if $\gamma_i \neq 0$, then the impact of past shock is asymmetric.

The Exponential GARCH (EGARCH) model:

The Exponential GARCH model was proposed by Nelson (1991) to overcome the problem of asymmetry in information flow. Its conditional variance equation is given by:

$$log(\sigma_t^2) = a_0 + \sum_{j=1}^{q} b_j log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} a_i \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \sum_{k=1}^{r}\gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{6.17}$$

The left-hand side is the log of the conditional variance, meaning the effect is exponential rather than quadratic and that the forecast of the conditional variance is nonnegative. If $\gamma_i \neq 0$, then the impact is asymmetric, like in the previous model. If $\gamma_i < 0$, it indicates the presence of a leverage effect.

The component GARCH(CGARCH(1,1)) model:

The CGARCH model, proposed by Engle and Lee (1993), separates the conditional variance into a long-run component and a transitory component:

$$\sigma_t^2 = q_t + a_1(\varepsilon_{t-1}^2 - q_{t-1}) + b_1(\sigma_{t-1}^2 - q_{t-1}), \tag{6.18}$$

$$q_t = a_0 + pq_{t-1} + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2). \tag{6.19}$$

Equation 6.18 defines the conditional variance and equation 6.19 is the time-varying long-run volatility. The difference between the conditional variance and the long-run trend, $\sigma_t^2 - q_t$, is the transitory or short-run component of the conditional variance:

$$\sigma_t^2 - q_t = a_1(\varepsilon_{t-1}^2 - q_{t-1}) + b_1(\sigma_{t-1}^2 - q_{t-1}). \tag{6.20}$$

In a classic GARCH (1, 1), if the sum of the coefficient of the conditional variance $(a + b) < 1$ then the conditional variance mean-reverts to the conditional variance at a rate of $(a + b)$, which is called the mean-reverting rate or the persistence rate. Instead the originality of a CGARCH (1, 1) is the estimation of a long-run volatility component using an AR process, in equation 6.19. If $0 < p < 1$ then the long-run volatility will converge to a constant level ${a_0}/{(1-p)}$. The transitory component mean-reverts to zero at a rate of$(a_1 + b_1)$ if $0 < (a_1 + b_1) < 1$. In this framework, the long-run component has a much slower mean-reverting process than the transitory component, i.e. the long-run component is more persistent: $0 < (a_1 + b_1) < p < 1$ (Engle and Lee, 1999, 477-478). The sufficient conditions for the process to be covariance stationary are that $p < 1$ and $(a_1 + b_1) < 1$.

The Component GARCH with Threshold (ACGARCH(1, 1)):

A threshold can be added to the CGARCH (Engle and Lee, 1993). The conditional variance is now defined as:

$$\sigma_t^2 = q_t + a_1(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})N_{t-1} + b_1(\sigma_{t-1}^2 - q_{t-1}), \tag{6.21}$$

$q_t = a_0 + p(q_{t-1} - a_0) + \varphi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$ Long-run volatility

N_{t-1} is an indicator for negative lag innovation, ε_{t-i}^2, $N_{t-i} = \begin{matrix} 1 \text{ if } \varepsilon_{t-i} < 0 \\ 0 \text{ if } \varepsilon_{t-i} > 0 \end{matrix}$

Like for the GJR model, the dummy included in the transitory component in equation 6.21 captures asymmetry in the conditional variance. A significant positive coefficient γ indicates the presence of leverage effect.

6.4.1 ARMA-GARCH models estimates

If a series exhibit ARCH characteristics, then the estimated of OLS estimator is unbiased but the standard errors of the coefficients are underestimated (Engle 2001, p. 157), which may lead to an over-rejection of a true null hypothesis (Hamilton 2008).

There are two ways to estimate an ARMA-GARCH process: first, as a two-step procedure, fitting a GARCH model on the residuals of the ARMA OLS estimates; or secondly, to estimate jointly the conditional mean and the conditional variance equation, using a Maximum Likelihood estimator. This method allows the incorporation of the conditional variance into the estimation of the conditional mean (Hamilton 2008).

In a classic GARCH model, the standardized residuals are assumed to be normally distributed (see above equation 6.14). However, a GARCH process does not always capture all the excess kurtosis exhibited by a series. The solution is then to consider residual distribution allowing for fat tails, such as the Student-*t* distribution or the Generalised Error distribution (GED) (see Bollerslev et al. 1992, p. 23; Tsay 2005, p. 108; Xekalaki and Degiannakis 2010, p. 164-166). Other distributions which also take into consideration skewness are proposed, such as the skewed generalized-*t*-distribution (see Harris et al. 2004).

In this section we will estimate jointly the ARMA-GARCH model, applying the ARMA structure identified for each series in the previous section. We will use the Maximum Likelihood estimator and the General Error distribution (GED) for the models' residuals. For each series, the seven models described above are considered, using a general to specific approach. The best model is chosen according to its performance on the Engle's LM test and the BDS test. If for the same series, different models are competing, then the more parsimonious one is chosen. It is worth noting that the diagnostic tests indicated similar models for log-return and excess return series.

A plot of the annualized conditional standard deviation is provided for each series after the estimation and diagnostic results table. As models are similar for both log and excess return series, only the plots for the excess returns' annualized conditional standard deviations are shown.

Period 02/01/1990 – 10/12/2010

For the whole period, the following models were chosen:

AEX: MA(3)-CGARCH(1,1);

BEL20: AR(1)-CGARCH (1, 1);

CAC40: MA(3)-CGARCH(1, 1).

Table 6.12 presents the estimates for the ARMA-GARCH models for the entire period. The CGARCH conditional variance is given by equation 6.19 for the long run variance and 6.20 for the transitory component.

Table 6.12: Estimation of ARMA-GARCH models for the entire period.

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
c_0	0.000627*** (0.000114)	0.000457*** (0.000114)	0.000202 (0.000133)	-0.000035 (0.000134)	0.000442*** (0.000136)	0.000277** (0.000136)
Dummy (Mean)	-	-	0.000271 (0.000199)	0.000396** (0.000200)	-	-
c_1	-0.018040 (0.013560)	-0.017499 (0.013560)	0.060924*** (0.013765)	0.062272*** (0.013762)	-0.037396*** (0.013588)	-0.036916*** (0.013592)
a_1	-0.048467*** (0.016697)	-0.048550*** (0.016663)	0.060075*** (0.022290)	0.059700*** (0.022219)	-0.057571*** (0.015707)	-0.057712*** (0.015687)
b_1	0.089508 (0.417379)	0.093618 (0.416257)	-0.520214** (0.217974)	-0.522217** (0.218110)	0.185332 (0.335405)	0.182309 (0.335454)
a_0	0.000196*** (0.000074)	0.000195*** (0.0000734)	0.000128*** (0.0000481)	0.000128*** (0.0000476)	0.000198*** (0.000038)	0.000198*** (0.0000377)
p	0.991126*** (0.004240)	0.991127*** (0.004224)	0.986251*** (0.006154)	0.986226*** (0.006130)	0.984491*** (0.004942)	0.984466*** (0.004931)
φ	0.102083*** (0.008587)	0.101702*** (0.008567)	0.127280*** (0.012171)	0.122888*** (0.021227)	0.090812*** (0.008912)	0.090510*** (0.008898)
Dummy (Var.)	-	-	0.0000007** (0.0000003)	0.0000007** (0.0000003)	-	-

Standard error in parenthesis. * significance at 10%, ** significance at 5%, *** significance at 1%

Table 6.13: Diagnostic tests for the ARMA-GARCH models, entire period.

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
Skewness	-0.430122	-0.429874	-0.642474	-0.639893	-0.343045	-0.345077
Kurtosis	5.265997	5.280279	10.83249	10.80741	5.151925	5.184167
Jarque-Bera*	0.000	0.000	0.000	0.000	0.000	0.000
Q res. (5)*	0.078	0.069	0.000	0.000	0.300	0.069
Q res. (10)*	0.011	0.008	0.004	0.003	0.337	0.008
Q Sq. Res. (5)*	0.500	0.510	0.987	0.988	0.646	0.655
Q Sq. Res. (10)*	0.873	0.880	0.999	0.999	0.729	0.737
Engle's LM (1)*	0.5135	0.5192	0.8450	0.8470	0.3398	0.3378
Engle's LM (5)*	0.6453	0.6249	0.9967	0.9970	0.7779	0.7856
BDS m=2*	0.3959	0.4015	0.8159	0.8100	0.1980	0.4015
BDS m=3*	0.5143	0.5171	0.8452	0.8343	0.1488	0.5171
BDS m=4*	0.8414	0.8442	0.9105	0.8997	0.2894	0.8442
BDS M=5*	0.9442	0.9413	0.9969	0.9956	0.2522	0.9413

**p*-values

The results from the diagnostic test (see table 6.13) are that the standardised residuals exhibit negative skewness and excessive kurtosis. The Q-statistics on the squared residuals and the LM test indicate no further autocorrelation in the variance of the residuals. Finally, according to the p-values of the BDS test, the null of iid in the standardized residuals cannot be rejected. Other models for the mean and the variance were considered to improve the Q-statistics of the residuals; however they failed the BDS test.

The estimations of the mean equation (table 6.12) include a significant intercept for each index return, and a significant AR term for the Belgian index and MA term for the French index.

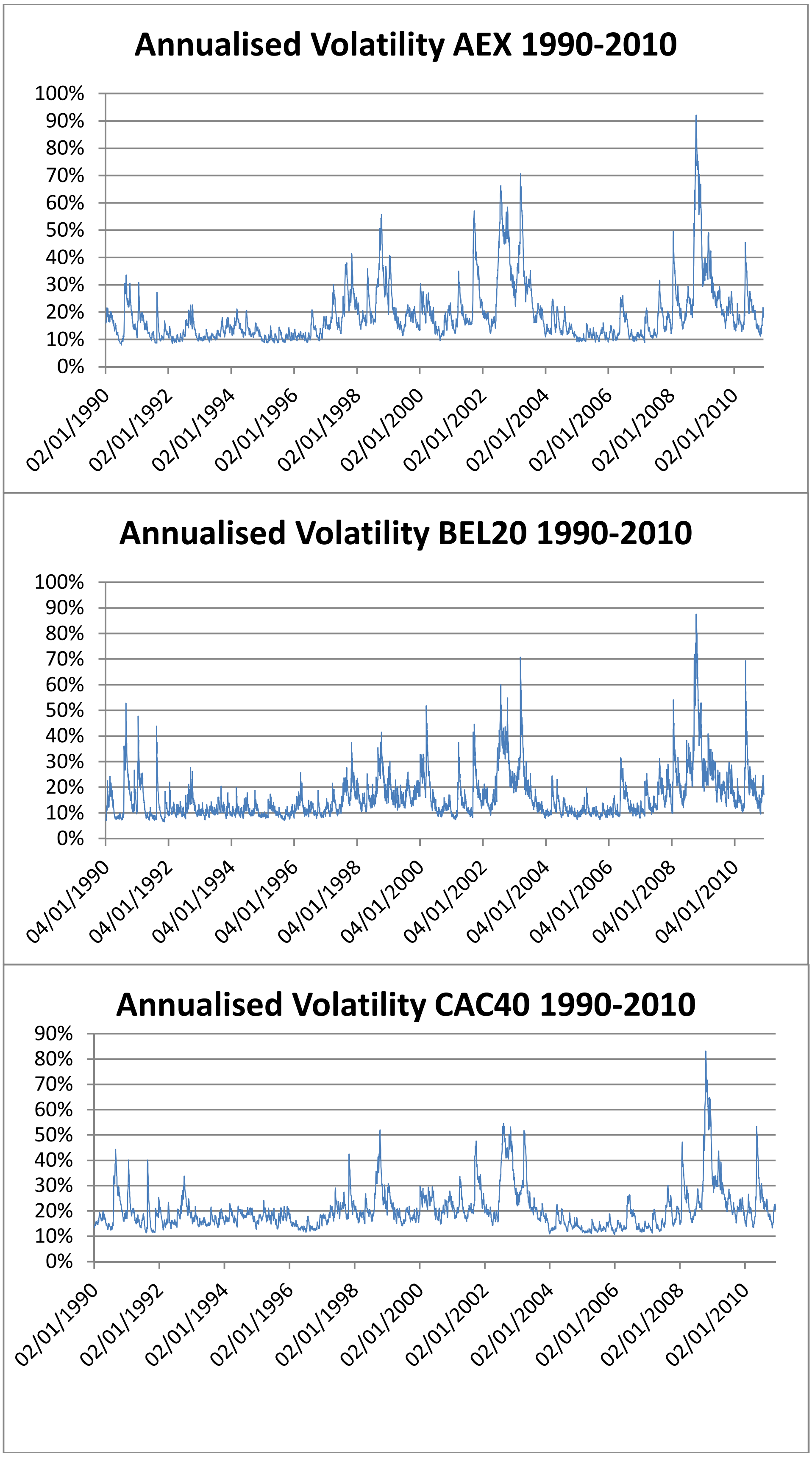
Following Engle and Lee (1999, 483), the interpretation of the CGARCH is as follows: 1. coefficients a_1 and φ represent the shock impacts on the short-run and the long-run components; 2. coefficient p estimates the mean-reverting parameter of the long-run component and; 3. the sum $(a_1 + b_1)$ captures the mean-reverting tendency of the short-run component.

The estimations of the coefficients a_1, p and φ (see table 6.12) are significant for all the index returns. Moreover, the values for a_1 are systematically larger than those for φ, indicating that the impact of transitory shocks is greater than permanent shocks. The estimations of the mean reverting parameters for the long-run component are all above 0.98 and are larger than the sum $(a_1 + b_1)$, indicating that the persistence of the transitory shocks is less than permanent shocks. These results capture a common pattern which is described by Engle and Lee (1999). Finally, the sufficient condition for covariance stationary process, i.e. $(a_1 + b_1) < 1$ and $\varphi < 1$, is there for all the index returns.

In order to control for the effect of the introduction of the Euro, the same models were estimated including a dummy variable with the value 0 before 01/01/1999 and 1 after the introduction of the common currency. The dummy variables were included in both the mean and the variance equation. All the estimates are presented in Appendix 6 (see section 10.6). The dummy variable was not significant in the mean and the conditional variance equations of the Dutch and French returns, indicating no significant effect due to the Euro currency. Hence, for these two countries, the processes were estimated again without the dummy variable. However, the dummy variable was significant in the equation of the conditional variance of the Belgian log-returns and in the equations of the mean and conditional variance of the Belgian excess returns (see table 6.12). This indicates that the introduction of the Euro had an impact on the returns series. But the sizes of the estimates for the dummy variable are very small, indicating that the effect is limited.

Figure 6.1 presents the plots of the annualised volatility of the excess return series for the entire period. For each series, peaks of annualized daily volatility appear during the periods: 1990-1992, 1997-1999, 2001-2003, 2007-2008 and in 2010. These periods are characterized by major political and economic events such as the first Iraq war (1990-1991), the Exchange rate mechanism (1992), the Asian crisis (1997), the Russian default (1998), the burst of the Dot.com bubble (2000), the terrorist attacks in New York (2001), the Argentinean crisis (2003), the Sub-prime crisis (2007-2008) and the sovereign debt crisis (2010).

Figure 6.1: Annualised volatility AEX, BEL20, CAC40, entire period.



Period 02/01/1990 31/08/2000

For the period preceding the Euronext integration, the following models were chosen:

AEX: MA (3)-ACGARCH (1, 1);

BEL20: AR(1)-CGARCH (1, 1);

CAC40: MA(1)-ACGARCH(1, 1).

The ACGARCH model is similar to the CGARCH model, but a dummy is included in the transitory component to assess asymmetry in the process (see equation 6.21).

Table 6.14: Estimation of ARMA-GARCH models for the pre-integration period.

Variable	AEX log return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
c_0	0.000604*** (0.0000375)	0.000461*** (0.000142)	0.000152 (0.000122)	-0.0000886 (0.000123)	0.0003888* (0.000203)	-0.0000682 (0.000203)
c_1	-0.014614*** (0.000215)	-0.013474 (0.018219)	0.093837*** (0.018406)	0.096587*** (0.018427)	0.0321707* (0.018697)	0.040315** (0.018465)
a_1	-0.052829** (0.026702)	-0.053443** (0.025922)	0.097562*** (0.037052)	0.097389*** (0.036922)	-0.019606 (0.026288)	-0.024218 (0.024207)
γ	0.142117*** (0.040222)	0.145481*** (0.039084)	–	–	0.071934** (0.024196)	0.084996*** (0.025258)
b_1	0.727424*** (0.094126)	0.732975*** (0.088301)	-0.478611** (0.216189)	-0.478400** (0.215880)	0.893619*** (0.050913)	0.877384*** (0.052072)
a_0	0.0000848*** (0.0000185)	0.0000837*** (0.0000182)	0.000113** (0.0000480)	0.000112** (0.0000466)	0.000133*** (0.0000141)	0.000129*** (0.0000123)
p	0.989857*** (0.003892)	0.990277*** (0.003728)	0.981122*** (0.010114)	0.980965*** (0.010044)	0.983320*** (0.007915)	0.982732*** (0.007711)
φ	0.049252*** (0.009610)	0.047736*** (0.009193)	0.123582*** (0.021359)	0.122888*** (0.021227)	0.031344*** (0.015265)	0.028225** (0.012721)

Standard error in parenthesis. * significance at 10%, ** significance at 5%, *** significance at 1%

Table 6.15: Diagnostic tests for the ARMA-GARCH models, pre-integration period.

Variable	AEX log-return	AEX excess return	BEL20 log- return	BEL20 excess return	CAC40 log- return	CAC40 excess return
Skewness	-0.549828	-0.541034	-0.883278	-0.884878	-0.414948	-0.41660
Kurtosis	6.394569	6.345760	16.20674	16.22905	6.329307	6.323519
Jarque-Bera*	0.00	0.00	0.00	0.00	0.00	0.00
Q res. (5)*	0.265	0.243	0.009	0.011	0.093	0.104
Q res. (10)*	0.025	0.019	0.008	0.010	0.045	0.052
Q Sq. Res. (5)*	0.794	0.791	0.956	0.957	0.971	0.970
Q Sq. Res. (10)*	0.989	0.989	0.998	0.998	0.852	0.846
Engle's LM (1)*	0.5483	0.5238	0.8071	0.8086	0.9922	0.9955
Engle's LM (5)*	0.8935	0.8912	0.9846	0.9851	0.9912	0.9909
BDS m=2*	0.2740	0.2550	0.8803	0.8941	0.5654	0.6220
BDS m=3*	0.6778	0.6098	0.8250	0.8373	0.4486	0.5171
BDS m=4*	0.9355	0.8426	0.6903	0.7606	0.6723	0.7748
BDS M=5*	0.5719	0.6617	0.6445	0.6955	0.7270	0.8684

*p-values

The models performed well in terms of the diagnostic tests (see table 6.15): no further autocorrelation or ARCH effect in the conditional variances and iid standardized residuals. The assumption of normality is rejected as the standardised residuals exhibit excess kurtosis and negative skewness. Finally, autocorrelation is captured in the mean equation until lag 5 (except for the Belgian index), but not at lag 10.

The mean equation (see table 6.14) for the Dutch index returns includes an intercept and a MA term, for the Belgian index no intercept but an AR(1) term and for the French index a MA term.

The conditional variance equation (see table 6.14) estimates $a_1$are significant only for the Dutch and Belgian index, implying a significant transitory shock for the Belgian returns. The estimates of the coefficients p and φ are significant for all indices. During this pre-integration period, the values of the coefficient φ which captures the long-run shocks are larger than those of a_1, the transitory shocks. Moreover, the estimates for b_1, the lagged transitory component, which can be interpreted as "old news", is significantly positive for the Dutch and French indices, indicating a positive impact of "old news" and significantly negative for the Belgian index, indicating a negative impact. The magnitude of the coefficient for the French ($b_1 = 0.727$) and Dutch ($b_1 = 0.89$) returns may translate long memory in the variance. Finally, the coefficient p is larger than the sum $(a_1 + b_1)$, hence the persistence of permanent shocks is larger than transitory shocks.

Finally, the models estimated for the Dutch and the French indices included a dummy variable in the transitory component equation to account for the asymmetric effect of shocks. The estimates of the coefficient of the dummy variable are significant and positive for both indices, indicating that there is a transitory leverage effect in the variance for the Dutch and French indices.

The GARCH processes are covariance stationary as the sum $(a_1 + b_1) < 1$ and $p < 1$.

Figure 6.2: Annualised volatility, AEX, BEL20, CAC40, pre-integration period.

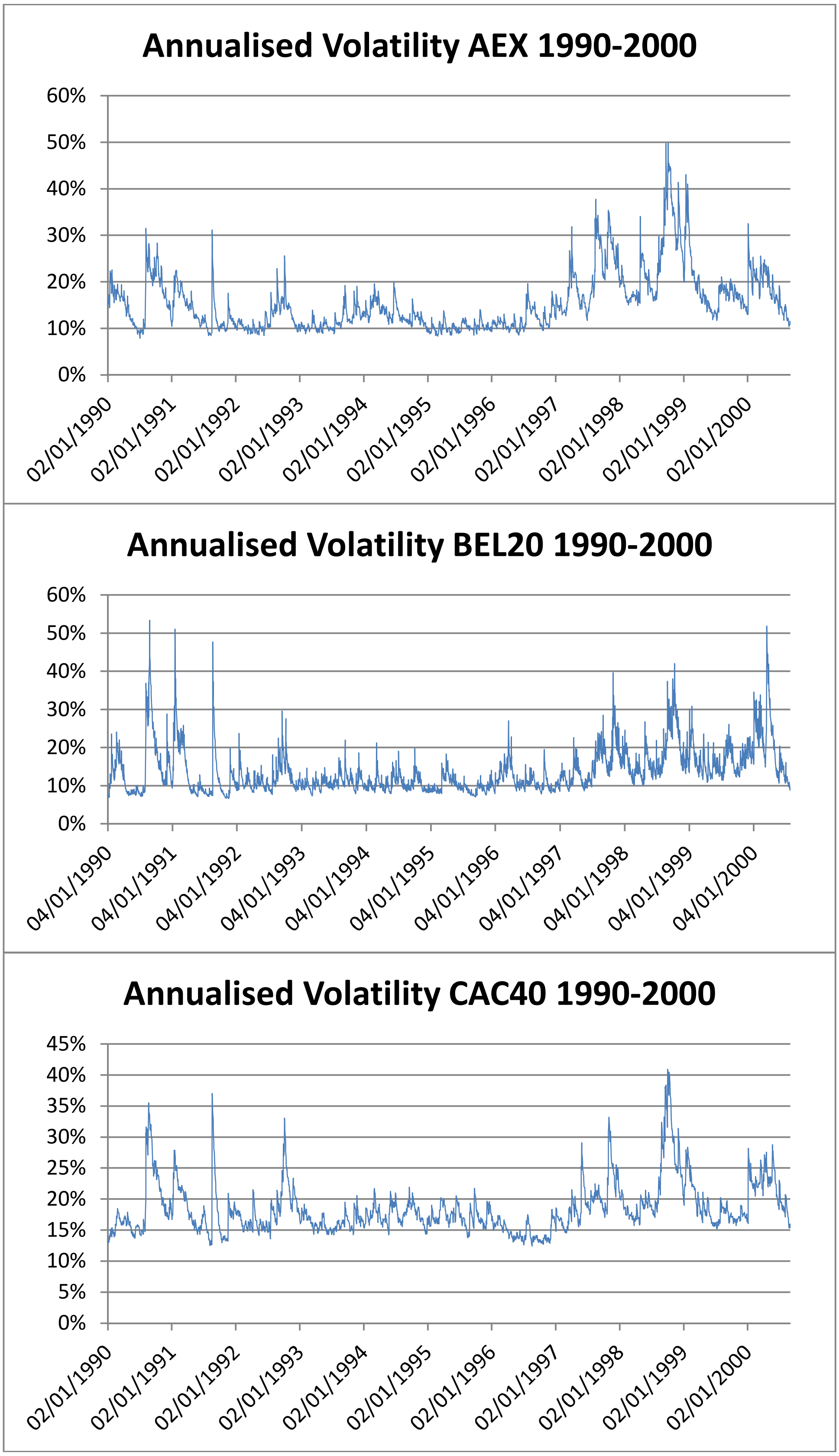


Figure 6.2 presents the plots of the annualised volatility for the indices excess returns during the pre-integration period. Peaks of daily annualized volatility appear in 1990, 1991 and 1992. These peaks are more acute for the Belgian stock market. These peaks correspond to the invasion of Kuwait by Iraq (August 1990), the operation Desert Storm (beginning of 1991) and the failure of the Exchange Rate Mechanism in the third quarter of 1992. The period 1993 to the beginning of 1997 is characterized by low volatility whilst from mid-1997 to early 2000 the daily volatility increases again. The peak of the volatility is 1998 for the AEX and CAC 40 and in early 2000 for the BEL20. The period 1997-1998 was marked by the Asian financial crisis (third quarter of 1997) and the Russian default on its debt and the aftermath on Long Term Capital Management hedge fund.

Period 01/09/2000 30/10/2002

For the integration period, the following models were estimated:

AEX: MA(5)-CGARCH(1, 1);

BEL20: AR(1)-ACGARCH (1, 1);

CAC40: MA(5)-CGARCH(1, 1).

Table 6.16: Estimation of ARMA-GARCH models for the integration period.

Variable	AEX log return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
c_0	-0.000789 (0.00493)	-0.000943* (0.000493)	-0.000387 (0.000381)	-0.000446 (0.000397)	-0.000659 (0.000534)	-0.000664 (0.000612)
c_1	-0.056041 (0.039237)	-0.055973 (0.039273)	0.127003*** (0.041741)	0.133600*** (0.042166)	-0.063077 (0.043716)	-0.050731 (0.043387)
a_1	-0.244425*** (0.042552)	-0.244362*** (0.042932)	-0.144974*** (0.050644)	-0.178033*** (0.045787)	-0.294805*** (0.027172)	-0.306540*** (0.036936)
γ	–	–	0.200010*** (0.055767)	0.222280*** (0.052493)	0.202230*** (0.068740)	0.193746*** (0.068214)
b_1	0.195852 (0.243085)	0.192824 (0.243913)	0.949751*** (0.069824)	0.967782*** (0.070266)	0.047787 (0.304647)	-0.024811 (0.300301)
a_0	0.000483 (0.000560)	0.000485 (0.000566)	0.000956 (0.006705)	0.002152 (0.015895)	0.000562 (0.000542)	0.001027* (0.000602)
p	0.985858*** (0.021157)	0.985927*** (0.021165)	0.998097*** (0.013843)	0.998917*** (0.008287)	0.991100*** (0.011238)	0.995575*** (0.004263)
φ	0.176878*** (0.028272)	0.176894*** (0.028384)	0.157645*** (0.046627)	0.180050*** (0.046339)	0.090708*** (0.013762)	0.103500*** (0.020383)

Standard error in parenthesis. * significance at 10%, ** significance at 5%, *** significance at 1%

Table 6.17: Diagnostic tests for the ARMA-GARCH models, integration period.

Variable	AEX log-return	AEX excess return	BEL20 log- return	BEL20 excess return	CAC40 log- return	CAC40 excess return
Skewness	-0.051868	-0.051488	-0.167016	-0.151070	-0.102195	-0.106625
Kurtosis	2.897852	2.897435	3.493602	3.468259	3.529796	3.475019
Jarque-Bera*	0.779	0.780	0.015	0.026	0.022621	0.041
Q res. (5)*	0.996	0.996	0.549	0.605	0.491	0.620
Q res. (10)*	0.995	0.995	0.579	0.623	0.469	0.614
Q Sq. Res. (5)*	0.121	0.122	0.050	0.079	0.103	0.125
Q Sq. Res. (10)*	0.075	0.075	0.292	0.359	0.053	0.058
Engle's LM (1)*	0.8710	0.8785	0.7866	0.8386	0.6375	0.7590
Engle's LM (5)*	0.1915	0.1931	0.0686	0.1083	0.1690	0.2088
BDS m=2*	0.8014	0.7985	0.8279	0.8404	0.4696	0.5000
BDS m=3*	0.7023	0.6907	0.8969	0.9126	0.8344	1.0000
BDS m=4*	0.7491	0.7494	0.9413	0.9074	0.5994	0.8441
BDS M=5*	0.5737	0.5812	0.9427	0.9999	0.7371	0.9457

**p*-values

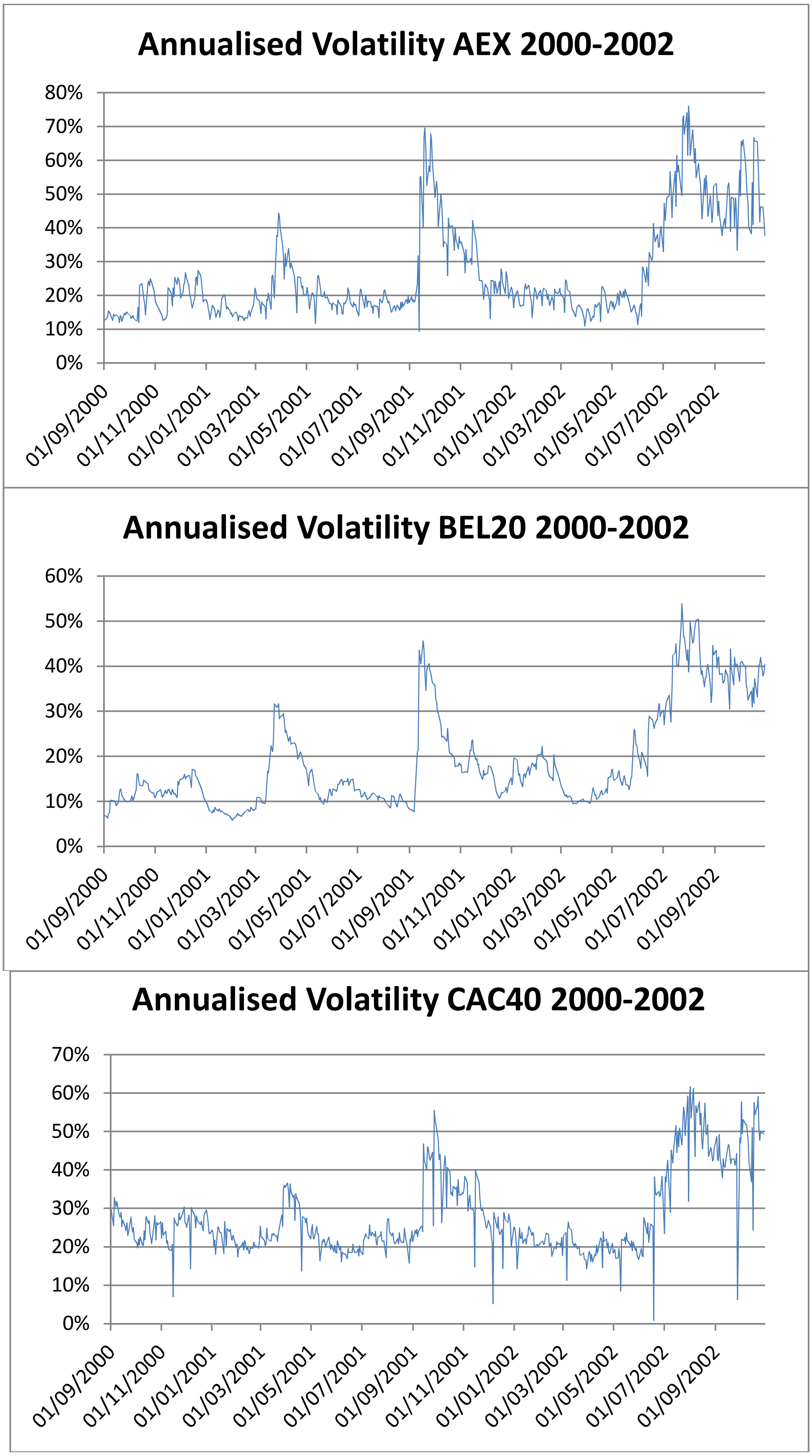
The models perform well in terms of diagnostic tests. No autocorrelation or ARCH effects remain in the conditional variances, the standardized residuals are iid and the Q-statistics reject the presence of autocorrelation in the standardized residuals (see table 6.17).

The mean equation (table 6.16) does not include a significant intercept and only the Belgian returns include a significant AR(1) term.

The coefficients a_1 , p and φ are significant for all the return series (table 6.16). The coefficient γ is significantly positive for the Belgian and the French returns, indicating a transitory leverage effect in their conditional variance. The values of a_1 , the impact of shocks on the transitory component, are larger than φ the impact of shocks on the long-run component, for the Dutch and the French indices but not for the Belgian index. The sum of $(a_1 + b_1)$ is smaller than the values of the coefficient p, indicating that the persistence rate of the long-run shocks is larger than the transitory shocks. Finally, b_1, the coefficient of the lagged transitory component, is significantly positive for the Belgian returns, indicating a positive impact of "old news" on volatility. Again, the magnitude of the coefficient may indicate long memory in the variance.

The sufficient condition for the models to be covariance stationary, i.e. $(a_1 + b_1) < 1$ and $p < 1$ are met.

Figure 6.3: Annualised volatility, AEX, BEL20, CAC40, integration period



The plots of the annualised volatility for the integration period are presented in figure 6.3. Volatility clustering appears during the third and fourth quarters of 2001, where the sudden increase corresponds to the terrorism acts in the USA (09/11) and their aftermaths, and during the third and fourth quarters of 2002, with a sharp and constant decrease of the indices price levels which stops in December 2003 only.

Period 01/11/2002 12/10/2010

For the period following the integration, the following models were considered:

AEX: MA(3)-CGARCH (1, 1);

BEL20: MA(3)-GARCH(1, 1) ;

CAC40 : ARMA(1, 1)-CGARCH (1, 1).

The conditional variance for a GARCH(1, 1) model is given by equation 6.14.

Table 6.18: Estimation of ARMA-GARCH models for the post-integration period

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 excess return	CAC40 excess return
c_0	0.000722*** (0.000195)	0.000630*** (0.000195)	0.000863*** (0.000174)	0.000776*** (0.000174)	0.000739*** (0.000143)	0.000652*** (0.000145)
c_1	-0.025091 (0.021879)	-0.025021 (0.019880)	-0.013577 (0.022288)	-0.013072 (0.022292)	-0.828286*** (0.058254)	-0.822878*** (0.061250)
c_2	–	–	–	–	-0.883460*** (0.047986)	-0.878077*** (0.050840)
a_1	-0.070746*** (0.016282)	-0.070706** (0.025105)	0.127048*** (0.014753)	0.127091*** (0.014771)	-0.108636*** (0.023304)	-0.108071*** (0.023302)
b_1	0.328240 (0.393216)	0.326750 (0.394170)	0.865512*** (0.013929)	0.865488*** (0.013943)	0.208382 (0.311120)	0.201403 (0.314544)
a_0	0.000238 (0.000164)	0.000238 (0.0000164)	0.0000017*** (0.00000047)	0.0000017*** (0.00000047)	0.000231* (0.000119)	0.000230* (0.000119)
p	0.991558*** (0.007098)	0.991569*** (0.007091)	–	–	0.988031*** (0.008021)	0.988090*** (0.007987)
φ	0.113535*** (0.013641)	0.113424*** (0.013634)	–	–	0.121552*** (0.015116)	0.121092*** (0.015091)

Standard error in parenthesis. * significance at 10%, ** significance at 5%, *** significance at 1%

The models perform well on all the diagnostic models (see table 6.19): no autocorrelation in the residuals and squared residuals. The standardized residuals exhibit no further ARCH effect and are iid.

The mean equations (see table 6.18) for all returns include a significant intercept and in the case of the French index, an ARMA (1, 1) term.

Table 6.19: Diagnostic tests for ARMA-GARCH models, post-integration period

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
Skewness	-0.245006	-0.244506	-0.326461	-0.325594	-0.331108	-0.330027
Kurtosis	3.799910	3.800801	4.401222	4.399412	4.080210	4.082661
Jarque-Bera*	0.00	0.00	0.00	0.00	0.00	0.00
Q res. (5)*	0.464	0.455	0.593	0.577	0.290	0.292
Q res. (10)*	0.642	0.633	0.805	0.797	0.487	0.491
Q Sq. Res. (5)*	0.543	0.544	0.581	0.590	0.352	0.351
Q Sq. Res. (10)*	0.664	0.661	0.852	0.858	0.884	0.883
Engle's LM (1)*	0.2879	0.2851	0.4236	0.4246	0.3665	0.3614
Engle's LM (5)*	0.6922	0.6931	0.7234	0.7312	0.6340	0.6327
BDS m=2*	0.2724	0.2716	0.8707	0.8585	0.2133	0.2123
BDS m=3*	0.3515	0.3578	0.6843	0.6748	0.3092	0.3067
BDS m=4*	0.5209	0.5319	0.8064	0.7791	0.3265	0.3249
BDS M=5*	0.5100	0.5209	0.7885	0.7662	0.2963	0.2960

*p-values

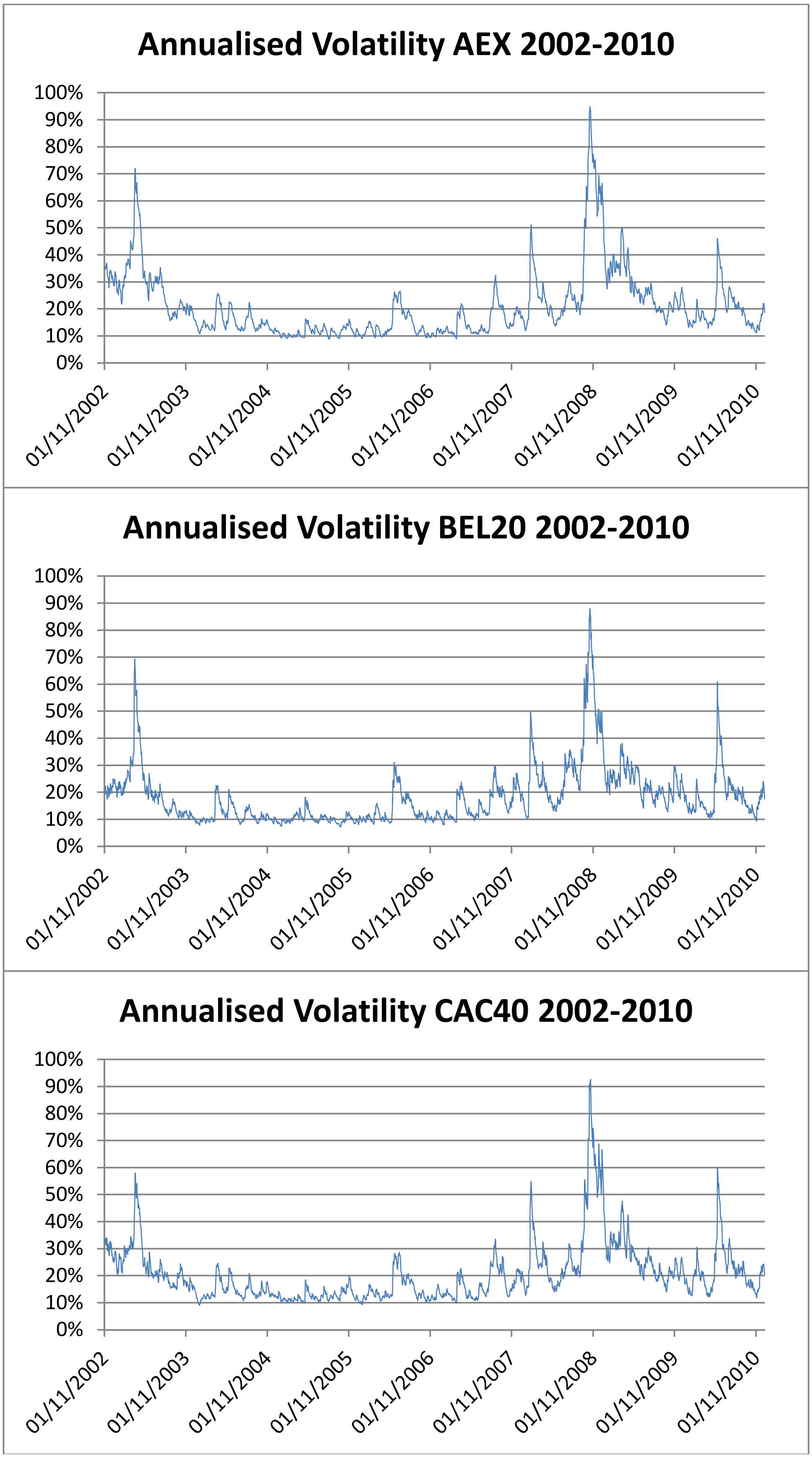
The estimates of the conditional variance equations are presented in table 6.18. For the Dutch and the French return indices, the coefficients a_1, φ and p are significant, but not b_1, the lagged transitory component coefficient. The values for a_1 are smaller than φ, indicating that the impact of the long-run shocks are larger than the transitory shocks. Finally, the values of the coefficient p are over 0.98 and much larger than the sum $(a_1 + b_1)$, hence indicating that the persistence of the transitory shocks is smaller than the long-run shocks.

In the case of the Belgian index, a simple GARCH (1,1) is found to be the best fit. The coefficient a_1 and b_1 are significantly positive, indicating a positive impact of recent and old news.

All the GARCH processes are covariance stationary as the sum $(a_1 + b_1) < 1$ and $p < 1$ for the CGARCH (AEX and CAC40) and the sum $(a_1 + b_1) < 1$ for the GARCH model (BEL20).

Figure 6.4 present the annualised volatility of the excess returns for the post-integration period.

Figure 6.4: Annualised volatility, AEX, BEL20, CAC40, post-integration period.



The period following Euronext integration begins with relatively high volatility, with a peak in the first half of 2003, corresponding to the beginning of the second Iraq war. For the period end of 2003 to end of 2006, the volatility is overall low, with the exception of a peak in 2005. Volatility increases in 2007, with a major peak of magnitude 80% to 90% in 2008, corresponding to the “sub-prime” crisis and the credit crunch that followed. After a couple of quieter months, volatility peaked again in 2010, during the national debt crisis and the uncertainty caused by the situation in Greece.

6.4.2 Discussion

The data generating process of each series is best captured with ARMA-GARCH models. This finding is similar to Hsieh (1991), Sewel et al. (1996), Al-Loughani and Chappel (1997), Panagiotidis (2005), and Willcocks (2009). From the recapitulative table 6.20, it is clear that the component GARCH model, occasionally with a threshold, seems to best fit the conditional variance of all but one return series (BEL20, for the period 2002-2010).

The CGARCH model allows the discrepancy between transitory, or short-run component and the long-run, or trend component of the conditional variance. In their original article, Engle and Lee (1999) believed that the shocks on the transitory component have a higher impact but a lower persistence than the shocks on the long-run component.

In this study, where CGARCH models were found to be the best fit, the rates of persistence of the shock on the long-run component are indeed larger than that of the shocks on the transitory component. This indicates that the transitory component, as expressed by equation 6.20, mean-reverts to zero faster than the long-run component mean-reverts to its stable level $^{a_0}/_{(1-p)}$ in all cases, as suggested by Engle and Lee (1999). However, the coefficient capturing the impact of the shocks on the transitory component was not systematically larger than the coefficient measuring the impact of shocks on the long-run component.

For the whole period (1990-2010) as well as for the period following the Euronext integration (2002-2010) none of the return series exhibit leverage effects. However, the Dutch and French returns show asymmetric treatment of bad news for the period prior to the Euronext integration (1990-2000) and the Belgian returns for the integration period (2002-2010).

Table 6.20: Models estimated

Period	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
1990-2010	MA(3) CGARCH(1,1)	MA(3) CGARCH(1,1)	AR(1) CGARCH (1, 1)	AR(1) CGARCH (1, 1)	MA(3) CGARCH(1, 1).	MA(3) CGARCH(1, 1).
1990-2000	MA (3) ACGARCH (1, 1)	MA (3) ACGARCH (1, 1)	AR(1) CGARCH (1, 1)	AR(1) CGARCH (1, 1)	MA(1) ACGARCH(1, 1)	MA(1) ACGARCH(1, 1)
2000-2002	MA(5) CGARCH(1, 1)	MA(5) CGARCH(1, 1)	AR(1) ACGARCH (1, 1)	AR(1) ACGARCH (1, 1)	MA(5) CGARCH(1, 1)	MA(5) CGARCH(1, 1)
2002-2010	MA(3) CGARCH (1, 1)	MA(3) CGARCH (1, 1)	MA(3) GARCH(1, 1)	MA(3) GARCH(1, 1)	ARMA(1, 1) CGARCH (1, 1)	ARMA(1, 1) CGARCH (1, 1)

The standardized residuals of all the models are not normal, exhibiting negative skewness and excess kurtosis, except for the Dutch returns for the integration period. Moreover, the Q-statistics on the residuals are significant for the whole period as well as for some returns in the first sub-period, indicating possible autocorrelation in the mean equation. However the models fully capture all the linear dependencies in the second and the third sub-periods. The difficulty of modelling the mean for the whole period may be due to structural breaks in the mean equation.

A dummy variable was included in the models to control for the introduction of the Euro, but it was found to be insignificant for the Dutch and French return series. However, the dummy variable was significant in the mean and conditional equation of the Belgian excess returns and in the conditional equation only for the Belgian log-returns. The size of the estimated dummy coefficient is extremely small, indicating a limited impact of the introduction of the common currency on the mean and conditional variance of the series.

All the estimated models capture fully the ARCH effect and estimate properly the conditional variance. Moreover, the standardized residuals of these models are iid. It is worth noting that for each series only one of the seven ARMA-GARCH models considered satisfied the iid criterion.

The long memory patterns in the volatility of the returns series presented in the previous chapter (see chapter 5) are fully captured by the ARMA-GARCH models as their standardized residuals are iid and do not exhibit further ARCH effects. This result is in line with Caporale and Gil-Alana (2004a) and Vougas (2004) who argued that simple ARMA-GARCH models may be better to capture long-memory patterns in volatility.

Finally, the plots of the annualized estimated daily volatility show that overall, the conditional volatilities of each series behave similarly, although less so for the BEL20 returns. A further investigation of the common behaviour of the series is undertaken in the next chapter.

The impact of the Euronext integration on the indices' returns is therefore not clear. The data generating process of the indices returns does not seem to change dramatically with Euronext. The series continue to exhibit heteroskedasticity or volatility clustering. On the other hand, in the post-integration period, none of the series seem to be affected by the leverage effect, i.e. the asymmetric treatment of good and bad news. This result however maybe due to relatively long periods of low variance in the sub-sample and different results may be found if one considers only the crisis period of the sub-sample (2007-2008 and 2010) as leverage effects are more acute during turmoil.

6.5 Main Findings

This chapter looks at the impact of the Euronext integration on the information efficiency of the Dutch, Belgian and French stock markets. More specifically, the main indices of the markets are used as proxies and the weak efficiency form is tested by analysing their data generating processes. A multistep strategy is applied, where linear and nonlinear models are estimated and a battery of diagnostic tests helps identify the best model for each series. The ultimate decision criterion is that the residuals from the estimates are iid.

Linear models, from the family of random walks or more general ARMA class, do not appear to explain the DGP of the AEX, BEL20 and CAC40 log- and excess returns. The diagnostic tests indicate the presence of heteroskedasticity in the residuals.

All the return series were explained using stochastic nonlinear models of the ARMA-GARCH class. All the models satisfy the Engle LM and the BDS tests, and hence exhibit iid residuals. However, the Q-statistics on the residuals for the models of the entire period and the pre-integration periods indicate some elements of autocorrelation in the mean equation. This might be caused by structural breaks in the mean equations.

Interestingly, only one of the conditional variance models proposed for each series passes the iid hurdle. Moreover, for each index the model chosen is the same for the log and the excess returns.

The ARMA-GARCH model captures well the pattern of long-memory process in the variance presented in chapter 5.

The impact of the Euronext integration on the series efficiency is mild. All indices continue to exhibit volatility clustering after the integration. However, the leverage effect disappears after the integration for all the series. Finally, the dummy variable capturing the impact of the introduction of the Euro is significant only for the Belgian returns series.

The next chapter looks into the impact of the Euronext integration on the interaction of the indices.

7 Multivariate Analysis

7.1 Introduction

The previous chapter investigated the potential changes in the indices following the Euronext integration. This chapter focuses on the nature of the relationships between the three indices forming the original Euronext. More specifically, it investigates the question: "Has the Euronext integration changed the interaction of the three indices?" Euronext integration involved creating a common framework for each stock exchange member, including one company, Euronext inc., common listing and trading rules, platform, source of information, etc. Such legal and operational integration implies that the three markets are now part of one entity. For the investors, this means a more attractive investment framework, with more investment solutions, easier access to information and trading operations. Ultimately, the merger should increase the attractiveness of the Euronext exchanges.

7.2 Empirical Framework

7.2.1 Hypotheses and research design

Hypotheses

The main hypothesis of this chapter is:

H_2: Euronext has increased the integration of the French, Belgium and Dutch stock markets.

As outlined in the literature review, there are different understandings of stock market integration and approaches to test it. In this paper, we define stock market integration as an increase in market co-movements. Moreover, two testing frameworks are adopted. First, cointegration analysis is used to explore the long-run relationship between the indices. The hypothesis is then:

$H_{2.1}$: Euronext integration has created long-run equilibrium between the French, Belgian and Dutch markets.

Parallel to long-run potential equilibrium, the short-run interactions between the markets are worth investigating. In particular, causality analysis, in a Granger sense, can give valuable insight into information flows between the markets. The hypothesis is:

$H_{2.2}$: Euronext integration has intensified information flows between the French, Belgian and Dutch markets.

However, cointegration analysis has been criticized for being a static approach and failing to capture the dynamic evolution of a process (Kim et al. 2005; Kearney and Lucey 2004; You and Daigler 2010). Hence, time-varying correlation is the second analysis. The hypothesis is:
$H_{2.3}$: Euronext integration has increased the correlation between the French, Belgian and Dutch markets.

The incorporation of Euronext was contemporaneous with the establishment of the European Monetary Union (EMU). In fact, it can be seen as a private response to the public policy of introducing the common currency. However, as these two events happened around the same time, it is difficult to distinguish between the impact of the Euronext integration and the introduction of the Euro on these stock markets. Therefore, a fourth market, the German stock exchange, is included in the analysis. Indeed, Germany is a core member of the Euro-zone but its stock exchange is not in the Euronext. Hence, the DAX30, Frankfurt's main index, is used as a control variable allowing differentiation between the impact of Euronext integration and the introduction of EMU on the French, Belgian and Dutch stock markets.

Research Design

The research design adopted to assess the long and short interdependence between the Stock Prices Indices (SPIs) is widely used in the literature (see table7.1 for a summary of interesting articles using cointegration studies relating to market integration). For example, see Shamsuddin and Kim (2003), Leong and Felmingham (2003) and Masih and Masih (1997, 2004). In particular, the research design includes bivariate and multivariate cointegration analysis to assess the long-run relationship. If variables are found to be cointegrated, i.e. if they exhibit long-run equilibrium, then an error correction model is estimated in order to capture their short-term adjustments to disequilibrium. Finally, Granger causality in a VAR or VECM framework, depending on whether the variables are cointegrated or not, helps to determine information flows.

Table 7.1: Studies assessing market integration using cointegration techniques.

Authors and Scope of Studies	Method and Data	Outcomes
Masih and Masih (2004): Dynamic linkages driving European stock markets before and after 1987.	*Method:* JJ multivariate cointegration analysis; Granger causality; error variance decomposition; impulse response function. *Data:* Monthly index prices for France, Germany, Netherlands, Italy and United Kingdom, divided into two sub-samples, pre- and post-crash.	No cointegration for the entire periods but one cointegrating vector in each sub-periods; lea-lag relationships changed significantly following the crash.
Masih and Masih (1997): Comparative analysis of the propagation of stock market fluctuations in alternative models of dynamic causal linkages.	*Method:* JJ multivariate cointegration analysis; Granger causality; error variance decomposition; impulse response function. *Data:* Monthly index prices for four Asian newly industrialized countries (NIC): Taiwan, Singapore, South Korea and Hong Kong; and four established markets: United States, Japan, United Kingdom and Germany. Four systems estimated, each comprised of the four NIC and one established markets.	Leading role of all the established markets on the NIC markets, ie they were the initial receptors of the exogenous shocks to the long-term equilibrium relationships.
Shamsuddin and Kim (2003): Integration and interdependence of stock and foreign exchange markets: An Australian perspective.	*Method:* JJ multivariate cointegration; impulse response function, VAR and VECM. *Data:* weekly index prices for Australian, Japan and the US, as well as the Australian dollar value of the Japanese Yen and US dollar. The sample is divided into three sub-periods: two pre-Asian and one post-Asian crisis.	Long-run relationship before the Asian crisis, but not after. Moreover, short-run dynamic linkages suggest that the influence of the US on the Australian market diminishes with the Asian crisis.
Leong and Felmingham (2003): The interdependence of share markets in the developed economies of East Asia.	*Method:* bivariate Engle Granger (EG) and Hansen cointegration tests, JJ multivariate cointegration, Granger causality. *Data:* daily index prices for Singapore, Korea, Japan and Taiwan.	Existence of long-run relationships and the degree of integration has increased between the markets during the 1990s.
Choudhry, Lu and Peng (2007): Common stochastic trends among Far East stock markets and the effects of the Asian financial crisis.	*Method:* JJ multivariate cointegration for long-run and band spectrum regression for short-run. *Data:* daily index prices for nine Asian stock markets and the US market. Sample is divided in three sub-periods: pre-crisis, crisis and post-crisis.	Long-run relationship during the three periods. But most important linkages and relationship are found during the crisis period.

Table 7.2: Studies using conditional correlation model to assess market integration

Authors and Scope of Studies	Method and Data	Outcomes
Kim, Moshirian, Wu Dynamic stock market integration driven by the European Monetary Union	*Method:* bivariate EGARCH-*t* model; Granger causality; regression analysis. *Data:* Daily index prices for 12 Euro-zone members, 3 non-Euro-zone members, Japan and US; a dummy variable for EMU; macroeconomic and financial variables and calendar effect dummies.	Increase of market integration following introduction of EMU; unidirectional causality from EMU to conditional correlations; integration favored by macroeconomic convergence associated with introduction of EMU.
Bartram, Taylor and Wang (2007): The Euro and European Financial Market dependence	*Method:* GJR-GARCH-*t* model and Gaussian copula to estimate joint probabilities. *Data:* daily stock index prices for twelve Euro-zone members and five European but not Euro-zone members; dummy variables.	Increase of integration between the Euro-zone members in early 1998, when EMU was announced. Lower integration for the non-members of the Euro-zone.
Kim, Moshirian, Wu (2006): International stock and bond market integration and the influence of the European Monetary Union.	*Method*: bivariate EGARCH-*t* model; Granger causality; regression analysis. *Data:* daily bond and stock indices prices for France for 4 Euro-zone and 3 non-Euro-zone members; macroeconomic and financial variables as explanatory variables.	Intra-stock and bond market has strengthen with the EMU, but inter-stock-bond market integration has decreased. The introduction of EMU has Granger-caused the segmentation between stock and bond markets within Europe, but not outside.
Hardouvelis, Malliaropoulos, Priestley (2006): EMU and European stock market integration	*Method:* multivariate BEKK-GARCH model. *Data:* weekly stock market prices and currency rates for 10 Euro-zone countries and the UK; financial variables.	Increase integration for the Euro-zone stock markets and but not for the UK market. The integration is Euro-zone specific phenomenon, independent of the world-market integration.
Egert and Kocenda (2011): Time varying synchronization of European stock markets	*Method*: Dynamic Conditional Correlation GARCH (DCC-GARCH). Data: Intraday prices for the Hungarian, Czech, Polish, German, French and UK main indices for the period 2003-2006.	High correlation between the developed EU markets, but low between the new EU markets or between the new EU markets and developed EU markets.

The interdependence between indices returns can be investigated using correlation analysis. However, traditional unconditional correlation measurements, such as Pearson or Spearman correlations, assume that the relationship remains the same throughout the periods. Hence, they do not track down the dynamics of the relationships. Similar to the GARCH models developed to measure the conditional variance of a time series, the multivariate GARCH (M-GARCH) models capture the conditional covariances of multiple time series. Moreover, Ayuso and Blanco (2001) showed that unconditional correlations are not appropriate to assess market integration. You and Daigler (2010) advocate that conditional or time varying correlation is a better estimate, especially as it provides a dynamic framework to assess markets' co-movements. Table 7.2 presents interesting studies using conditional correlation as core econometric methods.

Therefore, the research design for Hypothesis $H_{2.3}$ involves two measurements. First, unconditional correlation is estimated for each period using Pearson correlation. Second, time varying correlation between stock market indices' log-returnss is estimated using a multivariate version of the univariate GARCH model. The M-GARCH model estimates jointly the conditional variance and covariance of the different series in a given system, hence capturing the time varying correlation.

7.2.2 Cointegration and Vector Error Correction

Following Leong and Felmingham (2003), two approaches of testing for cointegration are adopted in this study. First, the long run equilibrium between pairs of indices is investigated by applying the Engle and Granger (EG) residuals based procedure. This allows the relationship between each pair of indices to be investigated individually. As the EG results are sensitive to the choice of the dependent and independent variables (Enders, 2004, p.347), each pair is tested twice, assigning the role of independent variable to each index.

The EG procedure involves two steps. First, a regression is run using the levels of the indices (equation 7.1). These levels are first tested to be $I(1)$.

$$SPI_t^D = \beta_0 + \beta_1 SPI_t^I + \varepsilon_t, \qquad (7.1)$$

where SPI_t^D is the dependent stock price index at time t, SPI_t^I is the independent stock price index at time t.

The second step involves testing the residuals of equation 7.1 for stationarity, using the ADF approach:

$$\Delta\hat{\varepsilon}_t = (\rho - 1)\hat{\varepsilon}_{t-1} + \sum_j^p \delta_j \, \Delta\hat{\varepsilon}_{t-j} + v_t. \qquad (7.2)$$

In Eviews 7, the ADF test statistic is based on a t-test of the null hypothesis of nonstationarity ($\rho = 1$), given by $\hat{\tau} = \frac{\hat{\rho}-1}{se(\hat{\rho})}$, where $\hat{\tau}$ denotes Engle's Tau.

The quantity $se(\hat{\rho})$ is the OLS standard error of the estimated $\hat{\rho}$, given by $se(\hat{\rho}) = \hat{s}_{\varepsilon}(\sum_t \hat{\varepsilon}_{1t-1}^2)^{-1/2}$.

If the residuals are stationary then the levels are said to be cointegrated, i.e. they have a long-run equilibrium and the regression is not spurious. In this case, the Granger representation theorem suggest that an Error Correction Model (ECM) can be estimated, including the first-differenced variables and the error correction term (ECT) from the cointegrating equations, which are the lagged values of the residuals from the cointegrating equation in 7.1. The ECT therefore captures the disequilibrium in the cointegrating relationship.

The second approach to cointegration involves the Johansen and Juselius (1990) (JJ) multivariate cointegration test. The JJ procedure is believed to be superior to the EG procedure (see Masih and Masih 2004; Kennedy 2009; Enders 2004) for the following reasons:

1. It does not assume the existence of at most a single cointegrating vector but tests for the number of cointegrating vector in a multivariate environment;
2. JJ is not sensitive to the choice of the dependent variable as it treats all variables as endogenous and does not depend on the ordering of the variables;
3. JJ provide appropriate statistics for the number of cointegrating vectors and test of restrictions for the coefficient of the vectors
4. Estimates and hypothesis testing of cointegrating vectors using OLS can be biased for small samples.

The JJ procedure is based on the identification of the rank of the m x m matrix Π in the following VAR system:

$$\Delta\mathbf{X}_t = \boldsymbol{\delta} + \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_{\mathrm{i}} \Delta\mathbf{X}_{t-i} + \boldsymbol{\Pi}\mathbf{X}_{t-k} + \varepsilon_t, \qquad (7.3)$$

where:

$\mathbf{X}_t$ is a m x 1 column vector of m variables (i.e. SPI),

$\boldsymbol{\Gamma}_{\mathrm{i}}$ and $\boldsymbol{\Pi}$ are coefficient matrices such as $\boldsymbol{\Gamma}_{\mathrm{i}} = -\sum_{\mathrm{j=i+1}}^{\mathrm{k}} \mathbf{A}_{\mathrm{j}}$ and $\boldsymbol{\Pi} = \sum_{i=1}^{k} \mathbf{A}_i - \boldsymbol{I}$,

$\boldsymbol{\delta}$ is m x 1 column vector of constants,

Δ is the difference operator,

k is the lag length.

If in equation 7.3 the matrix $\mathbf{\Pi}$ has rank zero, i.e. the sequences of variables are unit root processes, then no stationary linear combination can be found and the variables in the matrix $\mathbf{X}_t$ are not cointegrated. If the rank of $\mathbf{\Pi}$ is greater than zero, than there exists r possible stationary linear combinations. Moreover, the matrix $\mathbf{\Pi}$ can then be decomposed in two matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ of dimension m x r, such that $\mathbf{\Pi} = \boldsymbol{\alpha\beta'}$. The matrix $\boldsymbol{\alpha}$ includes the coefficients of the error correction terms for each of the equations in the VAR system. The matrix $\boldsymbol{\alpha}$ represents the speed-of-adjustment coefficients. The matrix $\boldsymbol{\beta}$ contains the coefficients of the r cointegrating vectors (i.e. that ensure that $\boldsymbol{\beta}'\boldsymbol{X_t}$is stationary).

The JJ method is to estimate the matrix $\mathbf{\Pi}$ from an unrestricted VAR and to test the restrictions implied by the reduced rank of $\mathbf{\Pi}$, i.e. to estimate the rank of $\mathbf{\Pi}$.
Two tests statistics are used to determine the number of cointegrating vectors: the “Maxiumum Eigenvalue” and the “Trace” statistics. Kennedy (2009, p.328) argues that the former is superior to the latter. When considering a system of three variables, the hypotheses being tested are as follows:

Maximum Eigenvalue		Trace	
Null hypotheses	Alternative hypotheses	Null hypotheses	Alternative hypotheses
$r = 0$	$r = 1$	$r = 0$	$r \geq 1$
$r \leq 1$	$r = 2$	$r \leq 1$	$r \geq 2$
$r \leq 2$	$r = 3$	$r \leq 2$	$r \geq 3$

Eviews 7 provides five testing frameworks for the JJ procedure, namely that:

1. the level of the variables have no deterministic trends and the cointegrating equations do not have intercepts;
2. the level of the variables have no deterministic trends and the cointegrating equations have intercepts;
3. the level of the variables have linear trends but the cointegrating equations have only intercepts;
4. the level of the variables and the cointegrating equations have linear trends;
5. the level of the variables have quadratic trends and the cointegrating equations have linear trends.

Only the first four frameworks are considered in this study. Indeed, the fifth assumes that the data are integrated of order 2.

Moreover, two multivariate systems will be estimated: system A, including only the three original indices from the Euronext; and system B which also include the German DAX index.

7.2.3 Temporal dependence

The temporal dependences of the indices can be evaluated using the broader Granger causality approach. According to Granger (1969), a variable x is said to Granger cause a variable y if x helps predicting y, i.e. the coefficients on the lagged values of the variable x are statistically significant:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-m} + \beta_1 y_{t-1} + \cdots + \beta_i y_{t-i} + \varepsilon_t, \qquad (7.4)$$

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-m} + \beta_1 x_{t-1} + \cdots + \beta_i x_{t-i} + u_t. \qquad (7.5)$$

The Granger causality test is a (Wald) F-statistic of the joint hypothesis for each equation:

$$\beta_1 = \beta_2 = \cdots = \beta_i$$

The null hypothesis is that the variable y does not Granger-cause x in equation 7.4 and that x does not Granger-cause y in equation 7.5.

If the variables are not cointegrated, than a Granger test of non-causality can be applied, using a simple VAR model:

$$\Delta \mathbf{X}_t = \mathbf{C} + \sum_{i=1}^{k} \mathbf{A}_i \, \Delta \mathbf{X}_{t-i} + u_t, \qquad (7.6)$$

where:

$\mathbf{X}_t$ is a m x 1 column vector of m variables,

$\mathbf{C}$ is a m x 1 column vector of constant terms,

$\mathbf{A}_i$ is a m x m matrix of coefficient,

Δ is the difference operator,

k is the lag length.

The Granger causality test is then a χ^2 Wald test. For each equation, it looks at the joint significance of the lagged values of the other endogenous variables in the equation, i.e. it assesses whether a variable is endogenous or exogenous.

However, if the variables are cointegrated, then Granger causality needs to be tested in the Vector Error Correction Model framework, such as equation 7.3. The difference between a VECM and an unrestricted VAR is the $\mathbf{\Pi X}_{t-k}$ component of the VECM equation in 7.3. If the variables are not cointegrated, i.e. the rank of the matrix $\mathbf{\Pi}$ is zero, the VECM collapses to the unrestricted VAR, as in equation 7.4.

According to Masih and Masih (1997, 2004) the analysis of the VECM allows for differentiation between the short- and long-run forms of Granger causality. Indeed, if the variables are cointegrated and a VECM of the form of 7.3 is estimated, then if the changes in the dependent variables force movements towards the long-run equilibrium, this can be seen as short-run causality. On the other hand, the long-run causality in the VECM is included in the lagged error correction term (ECT), as it includes information directly derived from the long-run cointegration equation. Therefore, the χ^2Wald test on the dependent variables in the VECM is used to indicate the short-term causality channels and the t-test on the lagged ECT to indicate the long-run causality.

7.2.4 Unconditional correlation: Pearson product-moment correlation

The Pearson product-moment correlation is:

$$\rho(X,Y) = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}, \tag{7.7}$$

Eviews 7 estimates the Pearson product-moment correlation as follows:

$$\hat{\rho}(X,Y) = \frac{\hat{\sigma}(X,Y)}{(\hat{\sigma}(X,X)\hat{\sigma}(Y,Y))^{1/2}}. \tag{7.8}$$

The test statistics is given by $t = \frac{r(n-k-1)^{1/2}}{(1-r^2)^{1/2}}$, where r is the estimated correlation and k the number of conditioning variables. In this study, the degrees of freedom are therefore $n-2$.

7.2.5 Conditional correlation: BEKK multivariate GARCH

The M-GARCH (Multivariate GARCH) models are a generalization of the univariate counterpart (for an extensive discussion, see Xekalaki and Degiannakis, 2010, chapter 11). More specifically, it can be defined as follows:

$$\mathbf{y}_t = \mathbf{B}'\mathbf{x}_t + \boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{\varepsilon}_t / \boldsymbol{I}_{t-1} \sim f[0, \mathbf{H}_t],$$

$$\mathbf{H}_t = g(\mathbf{H}_{t-1}, \mathbf{H}_{t-2}, \dots \boldsymbol{\varepsilon}_{t-1}, \boldsymbol{\varepsilon}_{t-2}, \dots), \tag{7.9}$$

where $(\mathbf{y}_t)$is a (n x 1) vector of the time series to be predicted; $E_{t-1}(\mathbf{y}_t) = \boldsymbol{\mu}_t$ is the conditional mean; $\boldsymbol{\varepsilon}_t = \mathbf{y}_t - \boldsymbol{\mu}_t$ is the innovation process of the conditional mean and has an (n x n) conditional covariance matrix $V_{t-1}(\mathbf{y}_t) = \mathbf{H}_t$; $\mathbf{B}$ is a (k x n) matrix of unknown parameters; $\mathbf{x}_t$ is a (k x 1) vector of endogenous and exogenous explanatory variables included in the available information set$\boldsymbol{I}_{t-1}$; $f\ (.)$ is the conditional multivariate density function of the innovation process and $g\ (.)$ is a function of the lagged conditional covariance matrices and innovation process (Xekelaki and Degiannakis, 2010, p. 445).

The innovation process can be written as follows:

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2}\mathbf{z}_t, \tag{7.10}$$

where $\mathbf{z}_t$is an (n x 1) vector of independent and identical distributed errors with $E(\mathbf{z}_t) = 0$ and $E\ (\mathbf{z}_t\ \mathbf{z}_t^{'}) = \mathbf{I}$.

Following the work of Baba et al. (1990), Engle and Kroner (1995) proposed a generalization of the univariate GARCH (p, q) to the multivariate environment, the BEKK(p, q) model, to model the conditional covariance matrix $\mathbf{H}_t$, as

$$\mathbf{H}_t = \mathbf{A}_0\mathbf{A}_0^{'} + \textstyle\sum_{i=1}^{q}(\mathbf{A}_i\,\boldsymbol{\varepsilon}_{t-i}\boldsymbol{\varepsilon}_{t-i}^{'}\mathbf{A}_i^{'}) + \sum_{j=1}^{p}\left(\mathbf{B}_j\mathbf{H}_{t-j}\mathbf{B}_j^{'}\right), \tag{7.11}$$

where $\mathbf{A}_0$ is a lower triangular matrix with $(\frac{n(n+1)}{2})$ parameters, $\mathbf{A}_i\mathbf{B}_j$ are (n x n) matrices with n^2parameters each.

A more parsimonious model is the Diag-BEKK (p, q) (Diagonal BEKK) where the matrices$\mathbf{A}_i$and $\mathbf{B}_j$ in equation (7.1) are restricted to being diagonal (Xekelaki and Degiannaki 2010, p. 448). The disadvantage of the parametrisation of the Diag-BEKK with regards to the original BEKK model is that it does not provide estimation of the volatility spillovers among the series.

Eviews 7 uses the maximum likelihood method to estimate the mean and the variances equations of the Diag-BEKK (p, q). In order to ensure that the conditional covariance is a positive semi-definite matrix, the full-rank method is chosen for estimating the parameters. An alternative method would be to use the scalar option which requires the estimation of fewer parameters. However, when applied, it provided explosive estimation of the conditional variance process for most of the series. Moreover, Eviews provides a choice for the function $f\ (.)$ in equation (7.9), ie the conditional multivariate density function of the innovation process: the multivariate normal and multivariate Student-*t* distribution. As seen in the previous chapter, the univariate processes were not normally distributed, hence the Student-*t* distribution is selected as the best density function for the innovation process.

A BEKK (1,1) model is estimated:

$$\mathbf{y}_t = \begin{pmatrix} \Delta CAC40 \\ \Delta BEL20 \\ \Delta AEX \\ \Delta DAX30 \end{pmatrix} = \begin{pmatrix} \beta_{0,1} \\ \beta_{0,2} \\ \beta_{0,3} \\ \beta_{0,4} \end{pmatrix} + \boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{\varepsilon}_t / \boldsymbol{I}_{t-1} \sim t[0, \mathbf{H}_t],$$

$$\mathbf{H}_t = \mathbf{A}_0 \mathbf{A}_0^{'} + \mathbf{A}_1 \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}_{t-1}^{'} \mathbf{A}_1^{'} + \mathbf{B}_1 \mathbf{H}_{t-1} \mathbf{B}_1^{'}. \tag{7.12}$$

The conditional variance of the log-return $y_{i,t}$ is the ith diagonal element of the matrix $\mathbf{H}_t$ in equation (7.12):

$$\sigma_{i,t}^2 = a_{0,i,i} + a_{1,i,i}\varepsilon_{i,t-1}^2 a_{1,i,i} + b_{1,i,i}\sigma_{i,t-1}^2 b_{1,i,i}\,, \tag{7.13}$$

and the conditional covariance between log-returns $y_{i,t}$ and $y_{j,t}$ is the (i, j)th element of $\mathbf{H}_t$ in equation (7.12):

$$\sigma_{i,j,t} = a_{0,i,j} + a_{1,i,i}\varepsilon_{i,t-1}\varepsilon_{j,t-1}a_{1,j,j} + b_{1,i,i}\sigma_{i,j,t-1}b_{1,j,j}. \tag{7.14}$$

Equation (7.13) is therefore a univariate GARCH (1, 1) capturing the conditional variance of the indices log-return and equation (7.14) the conditional covariance. The conditional or time-varying correlation is computed by standardizing the conditional covariance between two series by the cross-product of the square root of their conditional variances. An alternative model would be to estimate a TARCH/GJR GARCH (1, 1) model, but the results in chapter six indicate that the log-return series do not exhibit asymmetric behaviour for the whole period.

The model is estimated for the entire period and for the four indices' log-returns.
The analysis of the conditional correlation can be difficult. An interesting approach is developed by Filis, Degiannakis and Floros (2011) in a paper assessing the

relationship between stock market and oil prices, where the conditional correlation is analysed in the light of major economic and political events. A similar approach is developed and a framework of important events for the period 1990-2010 was developed prior to the estimation of the model.

Finally, following Kim et al. (2005), a Granger causality test between the conditional correlations, $\sigma_{i,j,t}$ and a dummy variable EMU, taking the value 1 from 01/01/1999 and 0 before this date, is conducted in order to determine the impact of EMU on the co-movements between the stock market indices log-returns. Different lag structures (2, 4, 6) are used.

7.3 Data and Sample

The data used for the cointegration testing procedure are the daily log-prices of the three Euronext indices. The data used for the error correction, the unrestricted VAR as well as the M-GARCH models are the log-returns of the indices. In the previous chapter, log-returns and excess returns showed extremely similar behaviour, hence in this chapter only log-returns are used.

The sample is divided in a similar way to that in the previous chapter: Entire period (03/01/1990-10/12/2010); Pre-Integration Period (03/01/1990-31/08/2000); Integration Period (01/09/2000-30/10/2002); and Post-Integration Period (01/11/2002-10/12/2010).

Figure 7.1 presents the plot of the log-prices of the three indices. The C-GARCH models estimated in the previous chapter for the three indices for the whole period (see chapter 6) are filtered using an asymmetric Christiano-Fitzerlgerald filter. The cycle of these C-GARCH are plotted in Figure 7.2. An examination by eye seems to indicate that the C-GARCH cycles synchronize after the Euronext integration.

Figure 7.1: Daily log-prices for CAC40, BEL20, AEX and DAX30 indices.

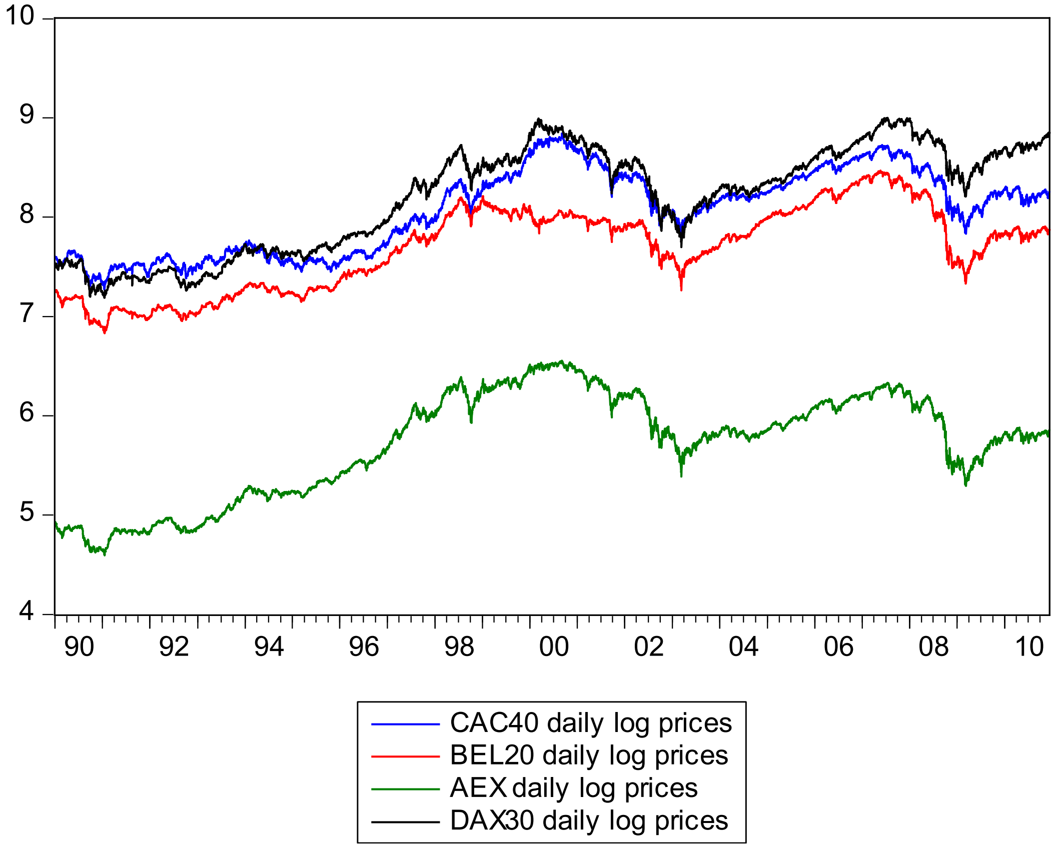
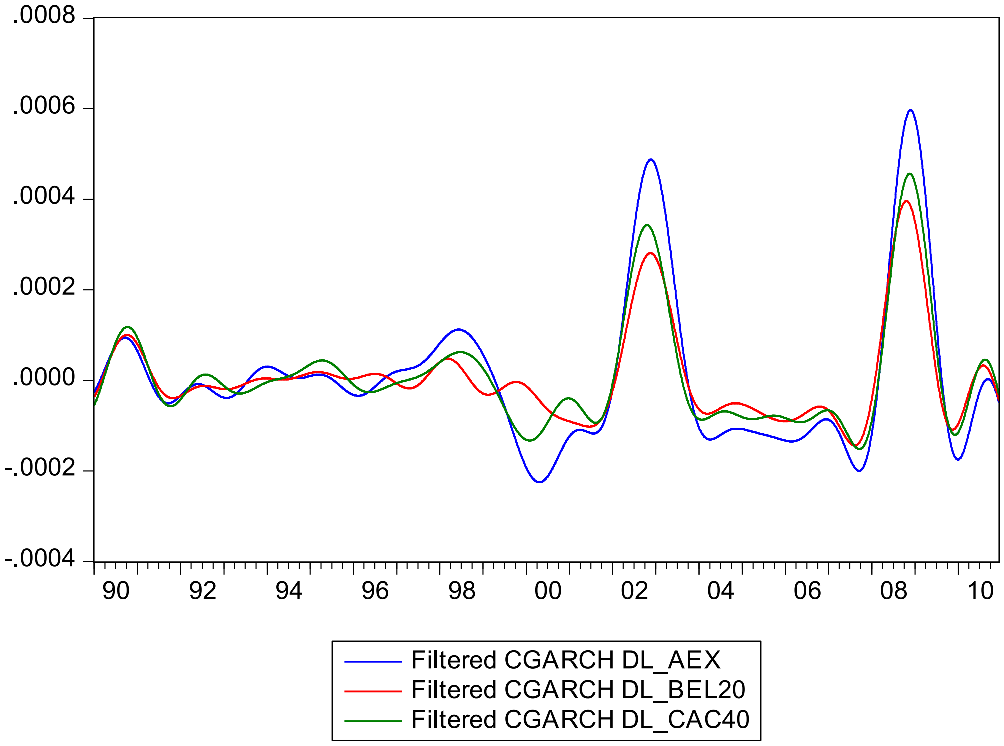


Figure 7.2: Daily C-GARCH filtered



7.4 Cointegration Testing

The results of the bivariate cointegration tests are presented in table 7.3. At 5% significance, there is no evidence of bivariate cointegration between the indices for the entire and the pre-integration periods. During the integration period, the French and Dutch and the German and the Dutch pairs are bivariate cointegrated, and during the post-integration period the French and Belgian present long-run equilibrium. There is therefore no continuity in the results before and after the Euronext integration. The results seem to be robust regarding the choice of the dependent variable.

Table 7.3: bivariate cointegration (Intercept, no trend)

$SPI^I \rightarrow SPI^D$	Entire period	Pre-integration period	Integration period	Post-integration period
$CAC40 \rightarrow BEL20$	-2.281715 (0.3822)	-1.060909 (0.8900)	-2.439735 (0.3074)	-4.739159 (0.0005)***
$BEL20 \rightarrow CAC40$	-2.043986 (0.3228)	-0.435351 (0.9671)	-2.411508 (0.3204)	-3.651813 (0.0214)**
$CAC40 \rightarrow AEX$	-1.799505 (0.6306)	-1.306312 (0.8294)	-3.789076 (0.0148)**	-3.102474 (0.0883)*
$AEX \rightarrow CAC40$	-1.862806 (0.5989)	-0.881794 (0.9209)	-3.864626 (0.0117)**	-3.268897 (0.0596)*
$BEL20 \rightarrow AEX$	-1.992081 (0.5322)	-2.716195 (0.1941)	-2.397468 (0.3269)	-3.060409 (0.0970)*
$AEX \rightarrow BEL20$	-1.834910 (0.6130)	-2.783507 (0.1713)	-2.180769 (0.4342)	-3.078507 (0.0932)*
$DAX30 \rightarrow CAC40$	-1.497904 (0.7641)	-1.444710 (0.7839)	-2.762661 (0.1795)	-0.098152 (0.9843)
$CAC40 \rightarrow DAX30$	-1.254702 (0.8442)	-1.704479 (0.6762)	-2.574318 (0.2493)	0.653251 (0.9977)
$DAX30 \rightarrow BEL20$	-1.868163 (0.5962)	-2.258986 (0.3937)	-3.147787 (0.0808)*	-0.228942 (0.9789)
$BEL20 \rightarrow DAX30$	-1.801211 (0.6298)	-2.135627 (0.4570)	-3.263385 (0.0615)*	-0.268630 (0.9770)
$DAX30 \rightarrow AEX$	-0.424858 (0.9678)	-2.744675 (0.1842)	-3.521688 (0.0317)**	-1.127374 (0.8759)
$AEX \rightarrow DAX30$	-0.143324 (0.9826)	-2.688332 (0.2041)	-3.459305 (0.0374)**	-0.907315 (0.9171)

Engle's Tau statistic (*p*-value in parenthesis). Equation with intercept and no trend. Lag length chosen with SBC.

Table 7.4 presents the results for multivariate cointegration testing for system A. Here as well, there is no cointegration for the entire and the pre-integration periods at 5% significance. However, there is evidence for long-run equilibrium during the integration period, if the cointegration equation includes an intercept and a trend, and during the post-integration period.

Table 7.5 presents the results for System B, which includes the German DAX index. The picture from system B is different as there is evidence of cointegration for the pre-integration and integration periods. In both cases, the cointegration equation included an intercept and a trend. There is no evidence supporting cointegration between the four indices for the entire and the post-integration periods.

Table 7.4: Multivariate cointegration tests, system A: CAC40, BEL20, AEX

Variables	Hypotheses		Test statistics	
Entire period, system A: CAC40, BEL20, AEX	H_0:	H_1:	Max. eigenvalue	Trace
	$r = 0$	$r > 0$	8.501307 (0.8705)	15.15888 (0.7697)
	$r \leq 1$	$r > 1$	3.7242078 (0.8872)	6.657575 (0.6178)
	$r \leq 2$	$r = 2$	2.9333367 (0.0868)*	2.933367 (0.0868)*
Pre-integration period, system A: CAC40, BEL20, AEX				
	$r = 0$	$r > 0$	11.84791 (0.5628)	15.69746 (0.7334)
	$r \leq 1$	$r > 1$	3.388120 (0.9176)	3.849551 (0.9153)
	$r \leq 2$	$r = 2$	0.461432 (0.4970)	0.461432 (0.4970)
Integration period, system A: CAC40, BEL20, AEX				
Intercept and trend	$r = 0$	$r > 0$	26.10843 (0.0459)**	43.89674 (0.0397)**
	$r \leq 1$	$r > 1$	10.82749 (0.5312)	17.78831 (0.3583)
	$r \leq 2$	$r = 2$	6.960823 (0.3486)	6.960823 (0.3486)
Post-integration period, system A: CAC40, BEL20, AEX				
	$r = 0$	$r > 0$	22.79331 (0.0289)**	37.03501 (0.0062)**
	$r \leq 1$	$r > 1$	11.67449 (0.1235)	14.24169 (0.0765)
	$r \leq 2$	$r = 2$	2.567202 (0.1091)	2.567202 (0.1091)

p-value in parenthesis

Table 7.5: Multivariate cointegration tests, system B: CAC40, BEL20, AEX, DAX30

Variables	Hypotheses		Test statistics	
Entire period, system B : CAC40, BEL20, AEX, DAX30	H_0:	H_1:	Max. eigenvalue	Trace
	$r = 0$	$r > 0$	8.511027 (0.9971)	18.16316 (0.9973)
	$r \leq 1$	$r > 1$	5.375869 (0.9924)	9.652134 (0.9849)
	$r \leq 2$	$r > 2$	3.712186 (0.8884)	4.276265 (0.8800)
	$r \leq 3$	$r = 3$	0.564079 (0.4526)	0.564079 (0.4526)
Pre-integration period, system B: CAC40, BEL20, AEX, DAX30				
Intercept and trend	$r = 0$	$r > 0$	43.56144 (0.0013)**	70.43802 (0.0127)**
	$r \leq 1$	$r > 1$	13.39410 (0.7728)	26.87658 (0.6882)
	$r \leq 2$	$r > 2$	10.25201 (0.5919)	13.48249 (0.6999)
	$r \leq 3$	$r = 3$	3.230476 (0.8481)	3.230476 (0.8481)
Integration period, system B: CAC40, BEL20, AEX, DAX30				
Intercept and trend	$r = 0$	$r > 0$	34.96359 (0.0218)**	72.30460 (0.0083)**
	$r \leq 1$	$r > 1$	19.97348 (0.2446)	37.34100 (0.1615)
	$r \leq 2$	$r > 2$	10.86093 (0.5277)	17.36752 (0.3988)
	$r \leq 3$	$r = 3$	6.506592 (0.3988)	6.506592 (0.3988)
Post-integration period, system B: CAC40, BEL20, AEX, DAX30				
	$r = 0$	$r > 0$	23.86142 (0.1396)	48.88221 (0.1355)
	$r \leq 1$	$r > 1$	11.86897 (0.5607)	19.02080 (0.4914)
	$r \leq 2$	$r > 2$	6.765442 (0.5173)	7.151827 (0.5601)
	$r \leq 3$	$r = 3$	0.386385 (0.5342)	0.386385 (0.5342)

p-value in parenthesis.

The estimates for the long term parameters βs are presented bellow for system A and B. The equations are normalised on the variable CAC40. Following Masih and Masih (2004), restrictions were imposed on the coefficient to test the null hypothesis that each coefficient is zero. The test is a likelihood ratio statistic, asymptotically $\chi^2(1)$ distributed. The results of the tests are presented underneath the estimates[4].

System A

1. Integration period

L_CAC40	**L_BEL20**	**L_AEX**	**TREND**
1.000000	0.200797	0.000218	0.000218
$\chi^2(1) = 13.65095$***	$\chi^2(1) = 1.683278$	$\chi^2(1) = 11.31765$***	

2. Post-integration period

L_CAC40	**L_BEL20**	**L_AEX**
1.000000	-0.761071	0.066641
$\chi^2(1) = 10.35353$***	$\chi^2(1) = 11.31643$***	$\chi^2(1) = 0.185858$

System B

1. Pre-integration period

L_CAC40	**L_BEL20**	**L_AEX**	**L_DAX**	**TREND**
1.000000	-2.306976	8.099595	-5.830969	-0.001779
$\chi^2(1) =$ 5.438315**	$\chi^2(1) =$ 11.15529***	$\chi^2(1) =$ 29.20559***	$\chi^2(1) =$ 26.69974***	

2. Integration period

L_CAC40	**L_BEL20**	**L_AEX**	**L_DAX**	**TREND**
1.000000	0.217735	-0.529342	-0.395077	0.000274
$\chi^2(1) =$ 13.66081***	$\chi^2(1) =$ 3.443412*	$\chi^2(1) =$ 4.525585**	$\chi^2(1) =$ 9.277674***	

For system A (excluding the German market), the French and Dutch markets enter significantly the cointegration equation, but not the Belgian market during the integration period. For the Post-integration period, the estimates for the French and the Belgian markets are significant, but not for the Dutch market.

As far as system B is concerned, the zero-loading restriction is rejected for all coefficients, indicating that all the markets enter the cointegration equations significantly for the pre-integration and integration periods.

4 *significance at 10%, ** significance at 5%, ***significance at 1%

Therefore, with the exception the Belgian market in system A, integration period and the Dutch market in system A, post-integration period, all markets adjust in a significant fashion to short-run disequilibrium. These short-run relationships are captured with the VECM shown underneath.

7.5 Temporal Dependence

Table 7.6 presents the estimation results from the Granger causality analysis using a VAR model for the pair of indices which are not "bivariate cointegrated" and table 7.7 the estimation results from the Granger causality analysis using a VECM for the pair indices which are cointegrated. The lag order of the VAR and VEC models were chosen according to the Schwarz Bayesian information Criterion (SBC). More precisely, at five percent significance, the results are as follows:

French-Belgian pair: the CAC40 Granger causes the BEL20 during the whole period. If there appears no causality during the pre- and integration periods, there is evidence of bi-directional causality during the post-integration period. Moreover, the ECT is significant in both cases.

French-Dutch pair: there is no evidence of causality for the entire and the integration periods, however the CAC40 Granger causes the Dutch index during the pre-integration period and there is strong evidence of bi-directional causality during the post-integration period.

Belgian-Dutch pair: there is evidence of bi-directional causality for the entire and the post-integration periods. There seems to be no temporal dependence during the pre-integration period and a unidirectional channel running from the Belgian to the Dutch indices during integration.

French-German pair: there is evidence of bi-directional causality during the entire and the post-integration periods. The French Granger causes the German index during the pre-integration period but this channel is reversed during the integration period.

Belgian-German pair: there is a unidirectional channel during the entire period, running from the Belgian to the German index, and during the integration period, from the German to the Belgian index. The pre-integration period is characterized by bi-directional causality and the post-integration by no Granger causality.

<u>Dutch-German pair</u>: there are unidirectional causality channels running from the Dutch to the German index for the entire and the post-integration periods, and from the German to the Dutch index for the integration and post-integration periods.

Therefore, the bivariate temporal dependences between the French, Belgian and Dutch indices vary and are limited before the Euronext integration, but there is strong evidence supporting bi-directional causality between the indices for the post-integration period. However, the interaction of these indices with the German index is different, as there are more causality channels before the integration than after.

Table 7.6: Bivariate Granger causality, estimated using a VAR model (Wald test of exogeneity)

Bivariate pairs	Entire period	Pre-integration period	Integration period	Post-integration period
$\Delta CAC40 \rightarrow \Delta BEL20$	5.150618 (0.0232)**	3.983302 (0.0460)	0.275557 (0.5996)	VECM
$\Delta BEL20 \rightarrow \Delta CAC40$	3.234087 (0.0721)*	2.683458 (0.1014)	2.252921 (0.1334)	VECM
$\Delta CAC40 \rightarrow \Delta AEX$	3.163525 (0.2056)	15.79131 (0.0001)***	VECM	11.23620 (0.0036)***
$\Delta AEX \rightarrow \Delta CAC40$	2.949887 (0.2288)	0.508251 (0.4759)	VECM	11.21257 (0.0037)***
$\Delta BEL20 \rightarrow \Delta AEX$	27.34185 (0.0000)***	3.298042 (0.0694)*	8.537128 (0.0035)***	23.08804 (0.0000)***
$\Delta AEX \rightarrow \Delta BEL20$	6.633748 (0.0363)**	0.166057 (0.6836)	1.826497 (0.1765)	8.754653 (0.0031)***
$\Delta DAX30 \rightarrow \Delta CAC40$	32.29254 (0.0000)***	2.987298 (0.0839)*	27.94341 (0.0000)***	31.23525 (0.0000)***
$\Delta CAC40 \rightarrow \Delta DAX30$	26.94310 (0.0000)***	106.0214 (0.0000)***	2.451581 (0.1174)	14.90967 (0.0006)***
$\Delta DAX30 \rightarrow \Delta BEL20$	0.006177 (0.9374)	5.796720 (0.0161)**	10.59970 (0.0011)***	0.423391 (0.5152)
$\Delta BEL20 \rightarrow \Delta DAX30$	10.84968 (0.0010)***	21.21003 (0.0000)***	0.063509 (0.8010)	2.484279 (0.1150)
$\Delta DAX30 \rightarrow \Delta AEX$	2.505986 (0.1134)	0.445588 (0.5044)	VECM	9.171730 (0.0025)***
$\Delta AEX \rightarrow \Delta DAX30$	25.27915 (0.0000)***	39.91472 (0.0000)***	VECM	0.992217 (0.3192)

χ^2values, *p*-value in parenthesis. * significance at 10%, ** significance at 5%, *** significance at 1%

Table 7.7: Bivariate Granger Causality, estimated using a VEC model (Wald test of exogeneity)

Bivariate pairs	Period	χ^2values, p-value in parenthesis	Estimated ECT, t-statistics in parenthesis
$\Delta CAC40 \rightarrow \Delta BEL20$	Post-integration	29.53962 (0.0000)***	0.018289 (2.92268)***
$\Delta BEL20 \rightarrow \Delta CAC40$	Post-integration	28.00005 (0.0000)***	0.029856 (4.34336)***
$\Delta CAC40 \rightarrow \Delta AEX$	Integration	2.415365 (0.1201)	0.071882 (2.25028)**
$\Delta AEX \rightarrow \Delta CAC40$	Integration	0.777697 (0.3778)	0.034255 (1.09581)
$\Delta DAX30 \rightarrow \Delta AEX$	Integration	35.38373 (0.0000)***	0.013789 (0.54413)
$\Delta AEX \rightarrow \Delta DAX30$	Integration	3.421386 (0.1807)	-0.039252 (-1.40805)

* significance at 10%, ** significance at 5%, *** significance at 1%

The results of the multivariate VECM analysis is presented in table 7.8 for system A (without the German index DAX) and 7.9 for system B (including the DAX as control variable). The VECMs were estimated in the form of 7.3, including the first differences of the indices and the ECT in lagged levels. The lag order was determined according to the Schwarz Bayesian information Criterion (SBC). The lag order was 2 lags for each VECM. At 5% significance, the results are as follows:

System A: During the integration period, there is evidence of short-run causality running from the changes in the Belgian index to the other indices, as well as from the Dutch index to the French index. During the post-integration period, the short-run causality from the Belgian index remains but not the one from the Dutch. Moreover, short-run causality also runs now from the French index to the other two indices. In the VECM framework, the ECTs capture the adjustments to the deviation from the long-run equilibrium. It is interesting to note that during the integration period, none of the ECTs are significant; however in the post-integration period all three ECTs are statistically significant, indicating that now all three indices bear the brunt of short-run adjustment to long-run equilibrium.

System B: During the pre-integration period, the short-run causality runs from the changes in the French and German index to all other indices, as well as from the Belgian to the German index. However, during the integration period only the short-run causality running from the German index remains, joined by the influence of the Belgian index on the Dutch, and the Dutch on the French. As far as the long-run causality is concerned, the ECTs in the first difference equations of the Belgian and

German indices are significant for the pre-integration period, indicating their influence on short-run adjustments to long-run equilibrium, but no ECTs are significant for the integration period.

Table 7.8: Multivariate VECM for System A (CAC40, BEL20, AEX)

Dependent variable	Short-run lagged differences			Estimated ECT, (t-statistics)
	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	ECT_{t-1}
Integration				
$\Delta CAC40$	-	5.333795 (0.0209)**	4.8512328 (0.0337)**	-0.044132 (-0.92377)
$\Delta BEL20$	1.017617 (0.3131)	-	2.567081 (0.1091)	-0.011536 (-0.32675)
ΔAEX	2.874759 (0.0900)	8.534710 (0.0035)***	-	0.041080 (0.84163)
Post-integration				
$\Delta CAC40$	-	21.41969 (0.0000)***	3.155847 (0.2064)	-0.041041 (-4.52211)***
$\Delta BEL20$	24.84224 (0.0000)***	-	4.257624 (0.1190)	-0.026128 (-3.16326)***
ΔAEX	24.60036 (0.0000)***	34.74535 (0.0000)***	-	-0.036438 (-3.83600)***

The ECTs were derived by normalising the cointegrating vectors on CAC40. *P*-value in parenthesis..
* significance at 10%, ** significance at 5%, *** significance at 1%

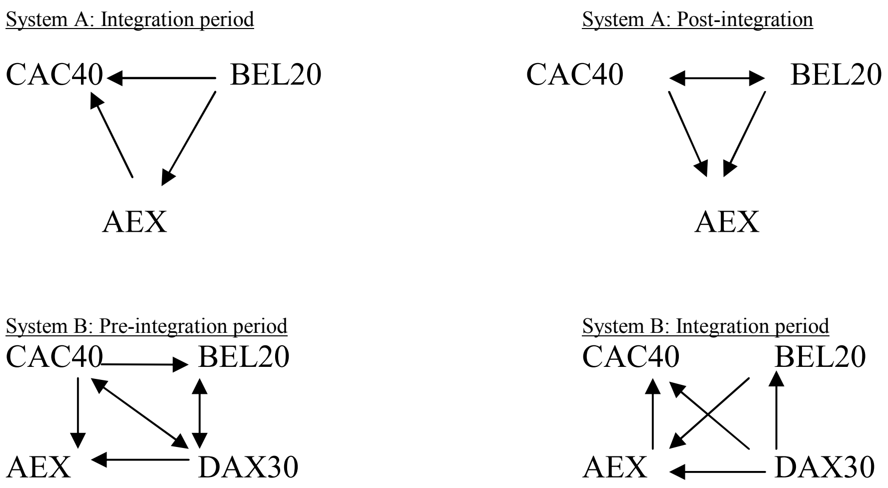
Table 7.9: Multivariate VECM for System B (CAC40, BEL20, AEX, DAX30)

Dependent variable	Short-run lagged differences				Estimated ECT, (t-statistics)
	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$	ECT_{t-1}
Pre-integration					
$\Delta CAC40$	-	4.677799 (0.0964)	0.296101 (0.8624)	22.63625 (0.0000)***	0.000552 (0.57128)
$\Delta BEL20$	10.30406 (0.0058)***	-	0.339564 (0.8438)	16.32305 (0.0003)***	0.001682 (2.22118)**
ΔAEX	20.06370 (0.0000)***	4.611676 (0.0997)	-	17.18763 (0.0002)***	-0.000673 (-0.78623)
$\Delta DAX30$	69.97847 (0.0000)***	6.625077 (0.0364)**	2.479209 (0.2895)	-	0.003548 (3.63336)***
Integration					
$\Delta CAC40$	-	5.280117 (0.0714)	6.674893 (0.0355)**	30.11676 (0.0000)***	0.035012 (0.92760)
$\Delta BEL20$	2.307191 (0.3155)	-	5.731758 (0.0569)	28.42633 (0.0000)***	-0.010422 (-0.37314)
ΔAEX	1.810968 (0.4043)	7.201737 (0.0273)**	-	35.61860 (0.0000)***	0.073390 (1.91381)
$\Delta DAX30$	1.301705 (0.5216)	4.352469 (0.1135)	3.7869303 (0.1506)	-	0.017521 (0.41219)

The ECTs were derived by normalizing the cointegrating vectors on CAC40. *P*-value in parenthesis.
* significance at 10%, ** significance at 5%, *** significance at 1%

Figure 7.3 summarizes the short-run causality channels for systems A and B. For system A, the French index is led by both the Belgian and the Dutch indices during the integration period, but during the post-integration period, it is the Dutch which is led by the French and Belgian indices. The Belgian index appears to have a leading role during both periods. For system B, it is the Dutch which is led by the German and the French markets during the pre-integration period and the French which is led by the Dutch and the German indices. The German market seems to keep a leading position during both periods.

Figure 7.3: Stock market lead-lag relationships based on short-run channels of Granger causality from VECMs



7.6 Correlation Analysis

Table 7.10 presents the estimation of the Pearson product moment correlation between the four indices' log-returns as measurement of the unconditional correlation. All the measurements are highly significant. It is evident that the association between the stock market returns increases over time: the last period exhibiting the highest unconditional correlation for each pair.

The log-returns of the French and the Dutch markets show the highest correlation measurements in all the periods except for the pre-integration period. The French and German and Dutch and German pairs' log-returns also exhibit relatively high degrees of association in all periods. Interestingly, measurements involving the Belgian log-returns systematically take a relatively lower value. This indicates that, in all periods, the Belgian market is relatively less correlated with the other markets.

Table 7.10: Pearson's correlation for the CAC40, BEL20, AEX and DAX30 log-returns

Entire period	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	1			
$\Delta BEL20$	0.754939 (0.0000)	1		
ΔAEX	0.857954 (0.0000)	0.793752 (0.0000)	1	
$\Delta DAX30$	0.802056 (0.0000)	0.699849 (0.0000)	0.808496 (0.0000)	1
Pre-integration	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	1			
$\Delta BEL20$	0.593777 (0.0000)	1		
ΔAEX	0.716575 (0.0000)	0.648028 (0.0000)	1	
$\Delta DAX30$	0.665973 (0.0000)	0.594062 (0.0000)	0.724033 (0.0000)	1
Integration	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	1			
$\Delta BEL20$	0.646977 (0.0000)	1		
ΔAEX	0.791921 (0.0000)	0.711479 (0.0000)	1	
$\Delta DAX30$	0.730990 (0.0000)	0.622849 (0.0000)	0.760875 (0.0000)	1
Post-integration	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	1			
$\Delta BEL20$	0.877357 (0.0000)	1		
ΔAEX	0.941224 (0.0000)	0.877501 (0.0000)	1	
$\Delta DAX30$	0.901167 (0.0000)	0.790970 (0.0000)	0.874277 (0.0000)	1

p –values in parenthesis.

The results of the Diag-BEKK GARCH (1, 1) model for the four indices log-returns are presented in table 7.11. The mean equations, comprised of a constant only, are significant for all indices. The coefficients of the indices' conditional variances are also significant. Moreover, the matrices $\mathbf{A}, \mathbf{B}$ and $\mathbf{H}$ were positive semi definite.

Table 7.11: Coefficients estimates for Diag-BEKK GARCH (1, 1)

Coefficients	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
Mean equation: b_0	0.00062 (0.00011)***	0.00055 (0.00009)***	0.00070 (0.00010)***	0.00079 (0.00012)***
Var/cov equation: a_0	6.12E-07 (9.94E-08)***	7.01E-07 (8.95E-08)***	6.03E-07 (9.04E-08)***	6.03E-07 (9.84E-0.8)***
Var/cov. equation: a_1	0.20165 (0.00472)***	0.21607 (0.00538)***	0.20756 (0.00494)***	0.19716 (0.00487)***
Var/cov. equation: b_1	0.97869 (0.00089)***	0.97323 (0.00124)***	0.97703 (0.00099)***	0.97951 (0.00092)***

Standard error in parenthesis. * significance at 10%, ** significance at 5%, *** significance at 1%

However, in the BEKK representation, the estimated coefficients have to be squared in the GARCH equations (see equation 7.13), yielding:

$$\sigma^2_{\Delta CAC40,t} = 0.0000006 + 0.040\ \varepsilon^2_{\Delta CAC40,t-1} + 0.957\sigma^2_{\Delta CAC20,t-1}$$

$$\sigma^2_{\Delta BEL20,t} = 0.0000007 + 0.046\ \varepsilon^2_{\Delta BEL20,t-1} + 0.947\sigma^2_{\Delta BEL20,t-1}$$

$$\sigma^2_{\Delta AEX,t} = 0.0000006 + 0.043\ \varepsilon^2_{\Delta AEX,t-1} + 0.954\sigma^2_{\Delta AEX,t-1}$$

$$\sigma^2_{\Delta DAX30,t} = 0.0000006 + 0.038\ \varepsilon^2_{\Delta DAX30,t-1} + 0.959\sigma^2_{\Delta DAX30,t-1}$$

The sum of the ARCH and GARCH coefficients is close to 1 for all index log-returns, indicating strong persistence of shock in the series volatilities. Alternative parsimonious models such as the scalar Diag-BEKK or scalar Diag-VECH were estimated, however the conditional variance equations for most of the series were explosive (i.e. the sum of the ARCH and GARCH coefficient was larger than one).

Following equation 7.14, the covariance equations are as follows:

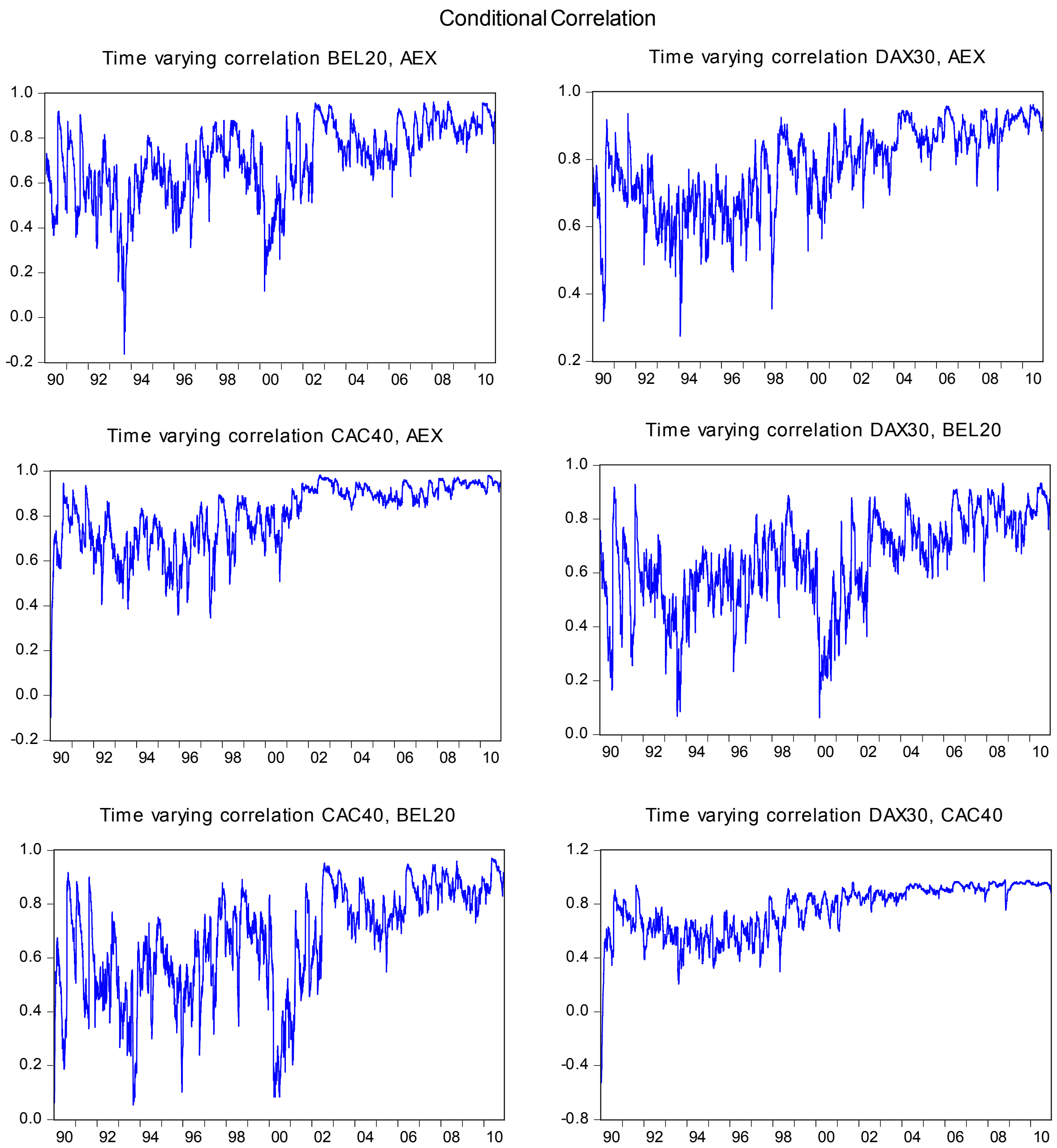
$$\sigma_{\Delta CAC40,\Delta BEL20,t} = 0.0000004 + 0.043\varepsilon_{\Delta CAC40,t-1}\varepsilon_{\Delta BEL20,t-1} + 0.952\sigma_{\Delta CAC40,\Delta BEL20,t-1}$$
$$\sigma_{\Delta CAC40,\Delta AEX,t} = 0.0000005 + 0.041\varepsilon_{\Delta CAC40,t-1}\varepsilon_{\Delta AEX20,t-1} + 0.956\sigma_{\Delta CAC40,\Delta AEX,t-1}$$
$$\sigma_{\Delta CAC40,\Delta DAX30,t} = 0.0000005 + 0.039\varepsilon_{\Delta CAC40,t-1}\varepsilon_{\Delta DAX30,t-1} + 0.958\sigma_{\Delta CAC40,\Delta DAX30,t-1}$$
$$\sigma_{\Delta AEX,\Delta BEL20,t} = 0.0000004 + 0.044\varepsilon_{\Delta AEX40,t-1}\varepsilon_{\Delta BEL20,t-1} + 0.950\sigma_{\Delta CAC40,\Delta AEX,t-1}$$
$$\sigma_{\Delta DAX30,\Delta BEL20,t} = 0.0000004 + 0.042\varepsilon_{\Delta DAX30,t-1}\varepsilon_{\Delta BEL20,t-1} + 0.953\sigma_{\Delta DAX30,\Delta BEL20,t-1}$$
$$\sigma_{\Delta AEX,\Delta DAX30,t} = 0.0000004 + 0.040\varepsilon_{\Delta AEX,t-1}\varepsilon_{\Delta DAX30,t-1} + 0.957\sigma_{\Delta AEX,\Delta DAX30,t-1}$$

The conditional covariance measurement is difficult to comprehend hence the conditional correlation, a scale invariant transformation of the former, is used. The conditional correlation is given by:

$$\rho_{\mathrm{i,j},t} = \frac{\sigma_{i,j,t}}{\left(\sigma_{i,t}^{2}\sigma_{j,t}^{2}\right)^{1/2}}.$$

Figure 7.4 presents the plots of the conditional correlations between the indices' log-returns. The first observation is that the conditional correlations are indeed non-constant. Moreover, all plots exhibit upward trends, with most of the correlation measures being positive. Only the pairs DAX30/CAC40 and CAC40/AEX are negatively correlated for a couple of days in early 1990 (03/01/1990-01/02/1990 for DAX30/CAC40 and 03/-12/01/1990 for CAC40/AEX) and the pair BEL20/AEX in mid-1993 (06-09/09/1993). Finally, the values of the conditional correlation coefficient are mainly above 0.4, except for some important drops, especially in mid-1993 and in 2000. These results are in line with the unconditional correlations measured with the estimations for the Pearson product-moment correlation coefficient in table 7.10.

Figure 7.4: Conditional correlation for the CAC40, BEL20, AEX, DAX30 log-return



The volatility of the conditional correlation measurements seems more important for the pre-integration and the integration periods than for the post-2002 sample. The coefficient of variation of the conditional correlation is used to track down the relative volatility of the conditional correlation. It is computed by standardizing the standard deviation of the conditional correlation by its average. This transformation yields a scale invariant measurement of the variability of conditional correlations, hence allowing for comparison.

The coefficients of variation are presented in table 7.12. The highest volatilities of the conditional correlations take place during the pre-integration period (for the pairs CAC40/AEX; CAC40/DAX30; DAX30/AEX; BEL20/AEX) and the integration period (for the pairs CAC40/BEL20 and BEL20/DAX30). The post-integration period is characterized by a much lower volatility for the conditional correlation between all pairs of index log-returns.

The pairs CAC40/AEX and DAX30/AEX exhibit the lowest variability during the entire and the post-integration periods. The pair DAX30/CAC40 is also very stable during the integration period. Finally, the conditional correlation coefficients of the pairs involving the Belgian stock index have the highest volatility in all periods (see table 7.12) as well as very similar overall shape (see figure 7.4).

Table 7.12: Coefficient of variation of the conditional correlation of the CAC40, BEL20, AEX and DAX30 log-returns

Entire period	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	0.0000			
$\Delta BEL20$	0.2952	0.0000		
ΔAEX	0.1775	0.2422	0.0000	
$\Delta DAX30$	0.2408	0.2599	0.1596	0.0000
Pre-integration	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	0.0000			
$\Delta BEL20$	0.3161	0.0000		
ΔAEX	0.1772	0.2646	0.0000	
$\Delta DAX30$	0.2582	0.2718	0.1534	0.0000
Integration	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	0.0000			
$\Delta BEL20$	0.3366	0.0000		
ΔAEX	0.0922	0.2490	0.0000	
$\Delta DAX30$	0.0813	0.2747	0.0835	0.0000
Post Integration	$\Delta CAC40$	$\Delta BEL20$	ΔAEX	$\Delta DAX30$
$\Delta CAC40$	0.0000			
$\Delta BEL20$	0.0893	0.0000		
ΔAEX	0.0370	0.0960	0.0000	
$\Delta DAX30$	0.0424	0.1015	0.0560	0.0000

The coefficient of variation are computed using the standard deviation of the conditional correlation between indices i, j log-returns and standardizing it by the average the conditional correlation.

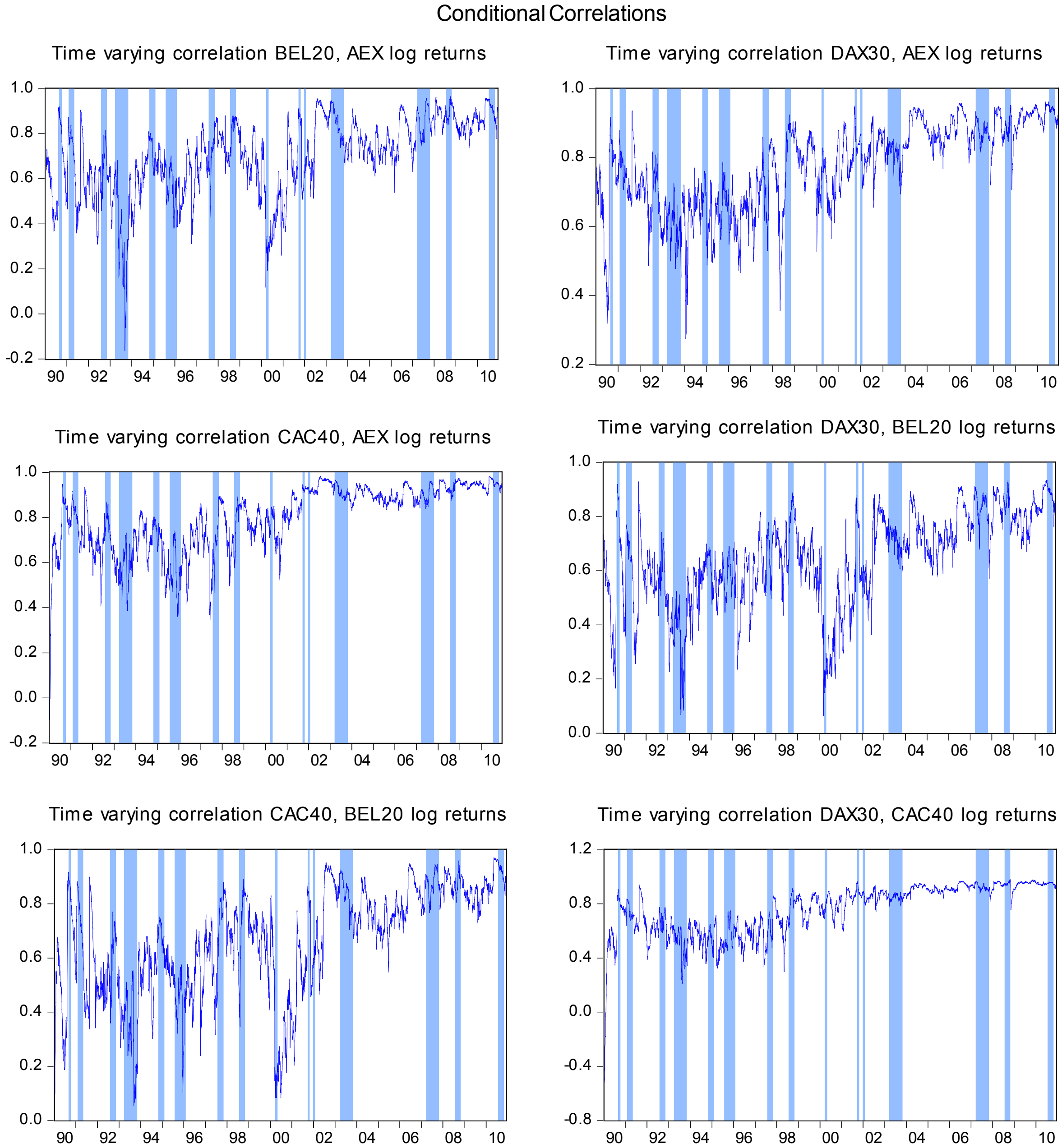
In order to analyse further the conditional correlations between the indices' log-returns, important political and economic events were chosen as landmarks. These events are summarized in table 7.13. Figure 7.5 presents the plots of the conditional correlation estimations with the periods corresponding to these important events in blue shade.

Table 7.13: Summary of important political and economic events

Period	Event
August 1990	Iraq invades Kuwait (02/08/1990)
First quarter 1991	Operation Desert Storm (January and February)
Third quarter 1992	Exchange Rate Mechanism (ERM) crisis: Black Wednesday (16/09/1992) UK and Italy forced to leave ERM
Second and third quarter 1993	Russian constitutional crisis.
Fourth quarter 1994	Tesobonos Mexican crisis. On 20/12/1994, Mexico announced 15% devaluation of the peso.
Third and fourth quarter 1995	Beginning of the Japanese banking crisis. During the summer 1995, the seven Jusen (housing loan companies) announced ¥6,410 billion losses.
Third quarter 1997	Beginning of the Asian financial crisis: Following speculative attacks, the Baht is devaluated on 02/07/1997. Contagion to Indonesia, South Korea, Philippines, Singapore, Malaysia, etc.
Third quarter 1998	Russian defaults on debt (17 August). Long Term Capital Market (LTCM) bankrupted.
March 2000	Dot-com bubble crash
11 September 2001	New York terrorist attacks
December 2001	International Monetary Fund stops payments to Argentina
Second and third quarter 2003	Iraq war II (19/03/2003)
Second and third quarter 2007	June: Bear Stearns and Fanny Mae August: BNP-Paribas freezes investment fund / FED and ECB inject money in the market September: Northern Rock rescued
Third quarter 2008	September 2008: Fanny MAC and MAE rescued by US (7th), Lehmann bankrupted (15th), deal BofA-Merrill (15th), Fed lends to AIG (16th), deal Lloyds-HBOS (18th), etc End of September-October 2008: Government intervention in US, Europe, Australia....
Third quarter 2010	Greek sovereign debt crisis (April and May)

Invasion of Kuwait and Iraq war I (1990-1991): In the days following the invasion in August 1990 as well as the beginning of operation Desert Storm in January 1991, all the conditional correlations increased to a high level (in between 0.8 and 0.9) and decreased afterwards.

Figure 7.5: Conditional correlation with political and economic events represented



Exchange Rate Mechanism Crisis (1992): All the correlation coefficients increased with the speculative attacks, especially around Black Wednesday. They decreased after the exit of Italy and the UK from the ERM.

Russian Constitutional Crisis (1993): This event had an inverse impact as all conditional correlations decreased. The drop was important during the peak of the crisis, in September and October 1993, especially for the pairs including the BEL20 log-returns.

Mexican Tesobono Crisis (1994): The correlation coefficients decreased as the crisis unfolded in the second part of December 1994, with the devaluation of the Mexican peso against the American dollar.

Japanese Bank Crisis (1995): Following the announcement of the losses of the Japanese banks in the summer of 1995, the correlation coefficients increased at first and then slightly decreased towards the end of the year. The pair CAC40, BEL20 log-returns dropped to values lower than 0.2 in December 1995.

Asian Crisis (1997): All the correlation coefficients increased sharply following the devaluation of the Thai baht against the American dollar in July 1997.

Russian Default (1998): Again, all coefficients increased sharply in the days around the announcement of the Russian default, in August 1998.

Dot.com bubble (2000): The burst of the dot.com bubble in March 2000 provoked mixed answers. The correlation coefficients involving the Belgian stock index log-returns dropped sharply, reaching values below 0.2. The coefficients of the other pairs increased, but not as importantly.

World Trade Center attacks (2001): The conditional correlation increased for all pairs in the days following 11/09/2001. The steepest increases involve pairs including the Belgian stock market log-returns.

IMF suspends Argentina loans (2001): Small increase in all coefficients except for the pair CAC40, AEX log-returns, whose coefficient remained stable.

Iraq war II (2003): The correlation coefficients increased with the beginning of the offensive in March 2003 and then decreased in May 2003.

Subprime crisis part 1 (2007): All the coefficients which were high in March 2007, slightly decreased in April but increased again with the announcements of the problems of Bearn Stearns and Fanny Mae in June, as well as in August with the Fed and ECB decisions to inject money in the financial system.

Subprime crisis part 2 (2008): Again, all the coefficients increased and remained high during the main part of the crisis.

Greek sovereign debt crisis (2010): The coefficients slightly decreased over the third quarter of 2010 however they all remained above 0.8.

In order to determine the impact of the EMU on the conditional correlations, Granger causality tests are conducted. As the Granger causality procedure is sensitive to lag structure, we follow Kim et al. (2005, p. 2494), and use lag 2, 4 and 6.

The results presented in table 7.14 support that the hypothesis "EMU dummy variable does not Granger cause $\sigma_{i,j,t}$" is rejected at 5% significance in all the lag structures, indicating a Granger causality channel running from EMU to each of the conditional correlations. The hypothesis "$\sigma_{i,j,t}$ does not Granger cause EMU" cannot be rejected at 5% in all lag structures, except for the pairs $\sigma_{\Delta CAC40,\Delta AEX,t}$ and $\sigma_{\Delta CAC40,\Delta DAX30,t}$ with lag 2.

Table 7.14: Granger causality test between conditional correlations and a dummy variable EMU

Hypothesis	**Lag 2, p −value**	**Lag 4, p −value**	**Lag 6, p −value**
$\sigma_{\Delta CAC40,\Delta BEL20,t}$ does not Ganger cause EMU	0.3697	0.7220	0.8374
EMU does not Granger cause$\sigma_{\Delta CAC40,\Delta BEL20,t}$	0.0451	0.0003	0.0001
$\sigma_{\Delta CAC40,\Delta AEX,t}$ does not Granger cause EMU	0.0491	0.1694	0.3697
EMU does not Granger cause$\sigma_{\Delta CAC40,\Delta AEX,t}$	0.0000	0.0000	0.0002
$\sigma_{\Delta CAC40,\Delta DAX30,t}$ does not Granger cause EMU	0.0410	0.1161	0.2804
EMU does not Granger cause $\sigma_{\Delta CAC40,\Delta DAX30,t}$	0.0000	0.0000	0.0000
$\sigma_{\Delta AEX,\Delta BEL20,t}$ does not Granger cause EMU	0.6356	0.9220	0.9750
EMU does not Granger cause $\sigma_{\Delta AEX,\Delta BEL20,t}$	0.0484	0.0376	0.0191
$\sigma_{\Delta DAX30,\Delta BEL20,t}$ does not Granger cause EMU	0.8622	0.9877	0.9906
EMU does not Granger cause $\sigma_{\Delta DAX30,\Delta BEL20,t}$	0.0415	0.0008	0.0144
$\sigma_{\Delta AEX,\Delta DAX30,t}$ does not Granger cause EMU	0.1154	0.3535	0.6051
EMU does not Granger cause $\sigma_{\Delta AEX,\Delta DAX30,t}$	0.0000	0.0000	0.0000

7.7 Discussion

In this section, the results are discussed in light of the a priori stated hypotheses.

$H_{2.1}$: Euronext integration has created long-run equilibrium between the French, Belgian and Dutch markets.

At the 5% significance level, the results of the bivariate cointegration analysis does not show a clear increase in cointegration between the French, Belgian and the Dutch indices following the Euronext integration, as only the BEL20 and the CAC40 exhibit long-run equilibrium. However, it is worth noting that at the 10% level of significance, all three indices are pairwise cointegrated in the post-integration period. Moreover, there is strong evidence against bivariate cointegration between the Euronext indices and the DAX30 index, a variable that controls for the EMU integration, for the post-integration period. This seems to indicate that the EMU has no excess impact on the relationship of the CAC40, BEL20 and AEX.

Table 7.15: Number of Cointegration Vectors for System A and System B

	Pre-integration	Integration	Post-integration	Entire period
System A	None	One	One	None
System B	One	One	None	None

The results from the multivariate analysis show that there is an increase in cointegration between the three Euronext indices (system A) following its integration, but not when including the DAX30 (system B). On the contrary, Euronext integration or the introduction of the EMU meant the end of the long-run equilibrium between the four indices. Table 7.15 presents a resume of the findings from the multivariate cointegration analysis.

The fact that long-run equilibrium between financial prices is not static but changes over time is documented in Masih and Masih (2004) Shamsuddin and Kim (2003) and Leong and Felmingham (2003). Indeed, shocks like the 1987 financial crisis (Masih and Masih) or the Asian financial crisis (Shamsuddin and Kim) can change the long-run dynamics.

$H_{2.2}$: Euronext integration has intensified information flows between the French, Belgian and Dutch markets.

The temporal dependences analysis depicts a similar picture. First, the bivariate Granger tests show that there is an increase in short-run causality between the three Euronext indices as all three exhibit bi-directional causality channels after integration. At the same time, the number of causality channels with the German DAX30 decreases. Then, the multivariate analysis shows the existence of a long-run causality between the Euronext indices after the integration, indicating that all three bear the brunt of adjustment to short-run disequilibrium.

In terms of short-run causality for system A, i.e. the Euronext indices, the French and Belgian indices seem to play a leading role. During the integration period, the Belgian index leads the two other indices, and during the post-integration period the Belgian and the French indices present synchronous channels of communications and are both leading the Dutch market. It is worth noting that only these two indices are pairwise cointegrated at 5% during the post-integration period.

Within system B, it is the German market which seems to play the leading role of picking up information and passing it to the other markets.

In the literature, changes in information flows between stock market indices are also documented (Masih and Maish 1997, 2004; Shamsuddin and Kim 2003). For example, Shamsuddin and Kim (2003) showed that the influence of the US market on the Australian market diminished after the Asian financial crisis.

$H_{2.3}$: Euronext integration has increased the correlation between the French, Belgian and Dutch markets.

Unconditional correlation measurements between the three Euronext indices' returns have increased after the integration. However, the association between these indices and the DAX30, the control variable, has also increased. In fact, the lower correlation measurements are recorded for pairs including the Belgian index returns.

The conditional correlations between the four stock indices' log-returns increase over time and their coefficients of variation indicate that the variability of the correlations decreased over time. The least volatile conditional correlations are measured between the French, Dutch and German indices' log-returns. The pairs involving the Belgian market are the most volatile during the whole period and in each sub period.

When looking at the effect of major political and economic events on the conditional correlations of the indices log-returns, it is interesting to note that the events of the pre-integration period yielded important changes in the conditional correlations. Indeed, except for the Russian constitutional crisis (1993) and the Mexican Tesobono crisis (1994), the political and economic shocks provoked a marked increase in the correlation coefficients. These coefficients decrease as the shocks are absorbed by the system. During the integration period, the most dramatic event, the World Trade Centre attacks, caused a similar pattern. However, the four events of the post-integration period did not induce marked changes in the conditional correlation coefficients, as these remained overall high (above 0.7 for the pair DAX30/AEX log-returns and above 0.8 for the pairs CAC40/AEX and DAX30/CAC40 log-returns) and stable, even during shocks. This pattern is the same for all the pairs during the post-integration period.

An interesting approach is to look at the results of the univariate analysis (chapter six) and of the conditional correlation analysis in the light of the economic and political events. The events having an important impact on the annualised conditional standard deviation of the indices (the Kuwait invasion and operation Desert Storm, the ERM crisis, the Asian crisis, the Russian default, the events of September 2011, the second war in Iraq, the two episodes of the Sub-prime crisis and the Greek sovereign debt crisis) were also characterised by a high conditional correlation between the indices. Hence, there is a direct link between high volatility and high correlation. This pattern is well-documented in the literature (see for example Solnik et al. 1996; Karolyi 2003; Das and Uppal 2004; Baele et al. 2004). This link can therefore limit the benefits of international diversification. Some authors (Solnik et al. 1996; Bekaert 2002a) believe that international diversification is still beneficial:

> As for the risk benefits, even though volatility is internationally contagious and correlation increases in periods of high volatility, international correlations remain at levels that are attractive from a diversification viewpoint (Solnik et al. 1996, p.32)

Indeed, Adjaoute and Danthine (2003) argued that that the European investors remain home biased.

Other authors (Das and Uppal 2004) suggest that international crisis contagion and systematic risk provide fewer opportunities for the investors to diversify their portfolios. Stiglitz (2010) argued that diversification and contagion are directly related and that wider financial integration increases the risk of contagion, especially in the event of a negative shock. Moreover, Fratzscher (2001) and Beale et al. (2004) believed that integration of the Euro area limits the diversification of the portfolio in the Euro-zone. Beale et al. (2004) explained the phenomenon by a further synchronisation of the business cycle of the Euro-zone countries and the convergence of the macroeconomic fundamentals. However, pointing out argued that the correlations of the EMU sector returns have decreased, they argued that there is greater potential in sector diversification than in geographic diversification (p.72).

These results show that during the post-integration period, there is an increase in correlation, as well as a more stable conditional correlation, between the indices' log-returns. However, this pattern cannot be directly attributed to Euronext integration as the pairs including the control variable, DAX30, follow the same behaviour. Egert and Kocenda (2011) using intraday data for the period 2003-2006 also found that the conditional correlation between the CAC40, DAX 30 and the UKX indices was high. Kim et al. (2005, 2006), Bertram et al. (2005), Hardouvelis et al. (2005) found that integration increased for the Euro-zone members. They all argued that EMU played an important role in the market's integration. Bertram et al. (2005) dates the beginning of the integration to early 2008, when the EMU was first announced.

In this paper, the results of the Granger causality tests between the EMU dummy variable and the indices' conditional correlations overwhelmingly show that there is a unidirectional causality channel between EMU and the conditional causalities. This result is in line with Kim et al. (2005, 2006).

It is therefore not possible to conclude that the Euronext integration has increased stock market integration directly as measured by the conditional correlation. It may however have played a role within the larger framework of EMU integration. Kim et al. (2005, 2006) demonstrated that financial integration is a result of the macro-economic convergence between the Euro-zone members, as well as a self-fuelling process (2005, p. 2500). Interestingly, the authors also showed that EMU Granger caused the segmentation between stock and bond markets within Europe and induced a flight to government bonds (2006, p. 1529). Bertram et al. (2005) and Hardouvelis et al. (2005) also showed that market integration is mainly a Euro-zone trait, as other European markets which are not part of the Euro-zone, do not show the same pattern. Hardouvelis et al. concluded that: "integration in Europe appears to be a Euro-zone-specific phenomenon, independent of possible simultaneous world-market integration" (p.390).

Concluding the discussion, the results of these different analyses can be collected together to answer the main hypothesis of this chapter:

H_2: Euronext has increased the integration of the French, Belgium and Dutch stock markets.

The results from the cointegration and temporal dependence analysis show that Euronext had an impact on the French, German and Dutch markets. However, the results from the correlation analysis, i.e. the dynamic analysis of the co-movements between indices' log-returns, do not support the hypothesis that Euronext had a direct impact on the stock markets. Indeed, results from the empirical work and from the literature review show that it was EMU, and not the Euronext, that Granger caused integration between these markets.

If, however, we see the Euronext integration as a private response to the European public policy for macro-economic and monetary convergence, then we can say that it indirectly impacted on the integration of the French, Belgium and Dutch stock markets. This conclusion is in line with Kim et al. (2005): "financial integration is largely a self-fuelling process dependent on existing levels of financial sector development" (p.2500)

7.8 Main Findings

This chapter examines the impact of the Euronext integration on the stock market interactions. The main hypothesis tested is that Euronext has increased the integration of the French, Belgium and Dutch stock markets. This main hypothesis is broken down into three hypotheses: 1. Has Euronext created a long-run equilibrium between the stock markets? 2. Has Euronext integration intensified information channels between the stock markets? 3. Has Euronext increased the co-movements between the stock markets?

The econometric methods used to test these hypotheses are derived from the literature. The JJ cointegration technique and the VEC models are used to assess long and short run relationship. The Granger causality framework is applied to assess the information channels. Finally, the BEKK-GARCH model is estimated to capture time-varying correlation. The econometric design is robust as it is comprised of both a static model, the cointegration technique, and a dynamic model, the M-GARCH process is a dynamic model.

The variables used are the log-prices and log-returns of the indices for the three Euronext stock markets. A control variable, the DAX30 German index, is used to account for the effect of EMU, as Germany is part of the Euro-zone but its main stock market is not a member of the Euronext.

For the static model, the original sample is divided into three sub-periods: pre-integration, integration and post-integration periods. For the dynamic approach, the model is estimated only once for the whole period.

The results of the cointegration analysis show that the Euronext indices have a long-run equilibrium during the integration and post-integration periods, but not for the pre-integration periods. The system which includes the control variable exhibits different behaviour, with long-run equilibrium before and during the integration, but not post-integration. This indicates that Euronext integration has an impact on its members.

The information channels have changed following Euronext integration, with the French and the Belgian indices having contemporary causality channels and leading the Dutch market.

The empirical and the conditional correlations between the three Euronext indices and the German index, the control variable have increased. At the same time, the volatility of the conditional correlations has decreased. These results show an increase in integration between these markets. A Granger causality test shows, however, that EMU has Granger caused this integration.

We therefore cannot conclude that Euronext has directly increased stock market integration. It is, however, part of a process of convergence, which includes public policies and private initiatives. In that sense, we can say that Euronext has indirectly or partially impacted on the integration of the French, Belgian and Dutch stock markets.

It is difficult to assess the impact of this market integration on the investors' propensity to diversify their portfolio. However, cointegration and the increase of dynamic correlation in the post-integration periods might decrease the choice of equity for investors. This is may be truer when one looks at the dynamic correlation around major events, where co-movements between the indices increase sharply, leaving investors with fewer alternatives.

8 Conclusions and Further Research

8.1 Research Context

The aim of this study was to assess the consequences of the merger of Euronext on its original constituent markets: the French, Belgian, and Dutch equity markets. More specifically, it investigated whether the merger was beneficial to market participants. Two research objectives were stated: one, assessing the market efficiency before and after the integration and the other, assessing the level of integration of the markets.

The research paradigm adopted in this thesis is a positivist research philosophy coupled with a deductive research approach. The literature review was therefore instrumental in the process of stating the hypotheses and building the econometric methodology.

The data used in the study are the daily closing prices for the French, Belgian, and Dutch national indices, CAC40, BEL20 and AEX, for the period 01/01/1990-10/12/2010. Two types of returns were computed for each index: the log-returns and the excess returns. The latter is calculated by deducting a proxy for the risk free rate, the one-month interbank rate, from the log-returns. Hence, the indices excess returns represent market premium rates.

The original data set is divided in three sub-periods: the pre-integration period (01/01/1990-31/08/2000), the integration period (01/09/2000-30/10/2002), and the post-integration period (01/11/2002-10/12/2010). The period 2000-2002 includes the gradual integration of the three stock markets into Euronext.

8.2 Review of the Main Findings

Preliminary tests show that the log-prices of each index are integrated of order one, $I(1)$, i.e. that the price levels have a unit root and the returns are stationary. These results are obtained using a robust procedure, the joint confirmation, which calls for the joint use of a unit root and a stationarity tests.

Moreover, the log-returns and excess returns were tested for long memory behaviour. Three tests were used: the Hurst R/S range, the GPH and the Robinson's procedure.

The results show no evidence of long memory in the returns. However, the returns' volatility exhibits long memory patterns.

Research objective 1:

The first research objective was to test the information efficiency of the French, Belgian and Dutch exchanges before and after Euronext integration. Related to this research objective, the following hypothesis is tested:

H_1: The French, Belgian and Dutch stock markets are more efficient following the Euronext merger.

In order to test this hypothesis, the DGP of each market is identified for each sub-period. The procedure to model the DGP is based on the iid residuals criterion. Three diagnostic tests are used: portmanteau Q-statistics, the Engle LM test and the BDS test.

First, the DGP of the indices returns were estimated using linear models, from the family of random walks or more general ARMA class. However, the residuals did not pass the diagnostic tests.

The long memory behaviour in the return volatility indicated the presence of non-linearity in the variance. Seven GARCH models are considered to capture conditional volatility: a simple GARCH model, a GARCH in Mean (GARCH-M), a GARCH with Threshold (TARCH), a GARCH in Mean with Threshold (TARCH-M), an Exponential GARCH (EGARCH), a Component GARCH (CGARCH) and a Component GARCH with Threshold (AGARCH) model. The EGARCH, the TARCH and the AGARCH belong to the family of asymmetric GARCH, which allow for different treatment of positive and negative shocks, hence recognizing the leverage effect.

All the return series were explained using stochastic nonlinear models of the ARMA-GARCH class. All the models satisfy the Engle LM and the BDS tests, hence they exhibit iid residuals. However, the Q-statistics on the residuals for the models of the entire periods and the pre-integration periods indicate some elements of autocorrelation in the mean equation. This might be caused by structural break in the mean equations.

The models estimated are as follows:

Period	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
Entire period	MA(3) CGARCH(1,1)	MA(3) CGARCH(1,1)	AR(1) CGARCH (1, 1)	AR(1) CGARCH (1, 1)	MA(3) CGARCH(1, 1).	MA(3) CGARCH(1, 1).
Pre-integration	MA (3) ACGARCH (1, 1)	MA (3) ACGARCH (1, 1)	AR(1) CGARCH (1, 1)	AR(1) CGARCH (1, 1)	MA(1) ACGARCH(1, 1)	MA(1) ACGARCH(1, 1)
Integration	MA(5) CGARCH(1, 1)	MA(5) CGARCH(1, 1)	AR(1) ACGARCH (1, 1)	AR(1) ACGARCH (1, 1)	MA(5) CGARCH(1, 1)	MA(5) CGARCH(1, 1)
Post-integration	MA(3) CGARCH (1, 1)	MA(3) CGARCH (1, 1)	MA(3) GARCH(1, 1)	MA(3) GARCH(1, 1)	ARMA(1, 1) CGARCH (1, 1)	ARMA(1, 1) CGARCH (1, 1)

Interestingly, only one of the conditional variance models proposed for each series passes the iid hurdle, i.e. there was no competing model. Moreover, for each index, the models chosen are the same for the log- and the excess returns.

In order to control for the impact of the introduction of the Euro, a dummy variable was included in the mean and the variance equations of each model. This variable was not significant for the Dutch and the French index, indicating no impact of the Euro on the DGP of the series. However, it was significant for the Belgian returns, but the small size of the dummy variable estimate indicated a very small impact.

Therefore, the impact of the Euronext integration on the series efficiency is mild. The asymmetric behaviour of the conditional variance, i.e. the leverage effect, disappears after the integration for all the series. But all indices returns continue to exhibit volatility clustering after the integration, indicating therefore that the markets are not more information efficient following Euronext merger.

Research objective 2:

The second research objective is to assess the level of market integration between the three exchanges before and after the Euronext integration. Multivariate time series econometrics techniques are used to research this objective. Additionally, in order to control for the effect of the introduction of the Euro, the German national DAX30 is included in the analysis. Indeed, the German stock market is from a country of the Euro-zone, but it is not a member of the Euronext exchange.

The following hypothesis is related to the second research:
H_2: Euronext has increased the integration of the French, Belgium and Dutch stock markets.

As this hypothesis is broad, it is broken down into three achievable hypotheses: $H_{2.1}$; $H_{2.2}$; $H_{2.3}$. The main findings for each hypothesis are presented below.

$H_{2.1}$: Euronext integration has created long-run equilibrium between the French, Belgian and Dutch markets.

Cointegration analysis is used to test $H_{2,1}$. Two different cointegration techniques are used: the Engle Granger bivariate and the Johansen Juselius multivariate methods.

At the 5% significance level, the results of the bivariate cointegration analysis does not show a clear increase in cointegration between the French, Belgian and the Dutch indices following the Euronext integration, as only the BEL20 and the CAC40 exhibit long-run equilibrium. Moreover, there is strong evidence against bivariate cointegration between the Euronext indices and the DAX30 index for the post-integration period. This seems to indicate that the EMU has no excess impact on the relationship of the CAC40, BEL20 and AEX.

The results for the multivariate cointegration analysis show cointegration between the three Euronext markets (system A) for the integration and post-integration period, but not for the pre-integration period. On the other hand, when including the control variable in the VAR (system B), there is evidence in favour of cointegration for the pre and integration period, but not for the post-integration period.

Therefore, the results of the two cointegration analyses indicate a reinforcement of the long-run equilibrium between the three Euronext indices following the integration of the Euronext. The fact that the DAX30 index does not enter the cointegration equations for the post-integration period indicates that this long-run equilibrium may be the result of the integration of the Euronext.

$H_{2.2}$: Euronext integration has intensified information flows between the French, Belgian and Dutch markets.

Hypothesis $H_{2.2}$ is tested with the analysis of the temporal dependences between the markets. This analysis is performed in a bivariate and a multivariate environment. In the latter, it is possible to differentiate between the long-run causality, captured by the ECT of the VECM, and the short-run causality, identified with the χ^2Wald test of exogeneity on the dependent variables in the VECM.

The bivariate Granger tests show that there is an increase in short-run causality between the three Euronext indices, as all three exhibit bi-directional causality channels after integration. At the same time, the number of causality channels with the German DAX30 decreases. The multivariate analysis shows the existence of a long-run causality between the Euronext indices (system A) after the integration, indicating that all three bear the brunt of adjustment to short-run disequilibrium.

In terms of short-run causality for system A, i.e. the Euronext indices, the French and Belgian indices seem to play a leading role. During the integration period, the Belgian index leads the two other indices, and during the post-integration period the Belgian and the French indices present synchronous channels of communications and are both leading the Dutch market. It is worth noting that only these two indices are pairwise cointegrated at 5% during the post-integration period.

Therefore, the integration of the Euronext has increased information flows between the three indices. The control variable presents a different behaviour, indicating that this increased in flow is not related to the introduction of the Euro.

$H_{2.3}$: Euronext integration has increased the correlation between the French, Belgian and Dutch markets.

Estimation of the unconditional and conditional correlations between indices' returns are used to test $H_{2.3}$. Unconditional correlation measurements between the three Euronext indices' returns have increased after the integration. However, the association between these indices and the DAX30, the control variable, has also increased.

The conditional correlations between the four stock indices' log-returns increase over time. Moreover, the coefficients of variation of the conditional correlation decreased over time. This indicates an increase in market's co-movements.

It is however not possible to attribute this increase in correlation directly to the integration of Euronext. The smallest unconditional correlations always involve Belgian returns. Moreover, the least volatile conditional correlations are measured between the French, Dutch and German indices' log-returns. The pairs involving the Belgian market are the most volatile during the whole period and in each sub period. Finally, a Granger causality test between the conditional correlation and a Euro dummy variable shows that EMU has Granger caused the increase in conditional correlations.

8.3 Conclusions

A first conclusion from this thesis is that the markets were not information efficient after Euronext integration, as the national indices' returns continue to exhibit volatility clustering in the post-integration period, especially during crises. For example, the volatility of the indices' returns peaks during the 2007-2008 financial crisis. The presence of GARCH effect in the volatility of the returns violates the weak-efficiency form of EMH as the information included in the variance may be used to forecast future index price. However, the fact that the leverage effects in the variance disappear after the merger can be seen as an efficiency improvement as then, the variance includes less information.

A second conclusion is that financial integration has increased between the markets but it is difficult to attribute it exclusively to Euronext. According to the results from the cointegration analysis, Euronext merger has played a role in the financial integration of the three markets. But, the results from the conditional correlation analysis do not provide the same evidence. We therefore cannot conclude that Euronext has directly increased the financial integration of the French, Belgian and Dutch stock markets. The merger is however part of a process of European convergence, which includes public policies and private initiatives. Each element of this process, the macro-economic convergence, the development of a common legal framework, the increase in exchange between European countries, the introduction of the Euro and the elimination of the exchange rate risk, is a factor pushing towards economic and financial integration. Euronext, by providing a common trading platform, is therefore a technological factor influencing integrated markets. As such, it can be interpreted that Euronext has indirectly or partially impacted on the integration of the French, Belgian and Dutch stock markets.

A third conclusion comes from integrating the findings and examining them in view of the major political and economic events. It is interesting to note that during crisis periods, the prices of the indices decrease, the volatility and the conditional correlation of the indices' returns increase. This situation may leave investors with fewer alternatives for portfolio diversification. Moreover, this pattern does not diminish in the post-integration period, indicating no change following Euronext integration.

Hence, Euronext integration has provided some benefits to market participants: it has slightly improved the information efficiency of the markets and provided a wider market for investments. However, during crisis periods, the increased financial integration may limit the possibility for market participants to internationally diversify their portfolios.

8.4 Limitations

The first limitation of this study is related to the difficulty of exactly dating the integration of the Euronext, as it is a long and gradual process. Moreover, it coincides with the introduction of the common European currency in the Euro-zone countries. It is therefore difficult to fully disentangle the impacts of these two events on the Belgian, French and Dutch indices.

The second limitation is related to the data set. This study uses stock indices, assuming that they are acting as proxies for the markets researched. However, the AEX, BEL20 and CAC40 truly represent only certain categories of the stock listed in these markets, the blue-chip shares. Hence, using different indices, such as for example small-cap index, sector index or even specific stocks may yield different results for the univariate and multivariate analysis.

Moreover, the national stock indices are also subject to survivorship bias. The study covers a 21-year period; hence the composition of each index has changed. However, because the indices' calculation criteria have not been modified during this time period and the window span is large, the impact of these changes is extremely small.

Finally, the study uses daily frequencies. Daily data include more information than longer frequency data (e.g. weekly or monthly), but also more noise. Hence, the data generating process of weekly or monthly data may be captured with less complex models in the univariate analysis. The multivariate analysis may also provide different results.

8.5 Further Research

The presence of GARCH effect in indices' returns is a stylised fact in finance, well-documented in the literature. The computation of the index, i.e. the aggregation of different share prices, may be causing or increasing this pattern. Hence, further research could focus on the impact of Euronext on sector indices or individual stocks. Also, it could investigate whether one can develop an investment strategy based on information included in the volatility of the returns that would yield systematic abnormal returns. In other words, are the other components of the French, Belgian and Dutch markets also information inefficient and is this lack of efficiency sufficient to generate economic profit?

The integrated results from chapter six and seven show that, during crises, the price levels of indices decrease, the conditional volatilities of the indices' returns increase as well as their conditional correlations. This situation may be problematic for investors who face an environment of falling prices and no alternative for diversification. This study does not address directly the problem of portfolio diversification or market contagion. Hence, further study could go in two different directions. First, it could assess the impact of the Euronext integration on diversification. In the literature, there is evidence of a shift from geographical diversification towards sector diversification. Therefore, a study including sector indices or hand-picked stocks from different sectors may address this question. Second, the problem of contagion induced by market integration could be addressed. Indeed, does this wider integration increase the systemic risk?

Moreover, the impact of the integration of Euronext could be also researched with a different econometric methodology. Time-domain instruments are the most popular in finance research. However, frequency-domain econometrics could be used. For example, wavelet analysis can help understand the DGP of a series by decomposing it into different cycles and measuring the intensity of each cycle at different times. Likewise, cross-wavelet analysis examines the relationship between variables by comparing their cycles and intensity. Another interesting econometric approach is the Singular Spectrum Analysis (SSA) which is essentially a non-parametric procedure, hence it addresses the problems of outliers and probability laws. SSA instruments can be used for both univariate and multivariate analysis.

Finally, it could be interesting to research the impact of the 2007 merger of Euronext with the largest exchange in the world, the New York Stock Exchange. However, another methodological issue may arise then as the merger was directly followed by the economic crisis of 2007/2008, which heavily affected stock markets and the financial world overall.

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10 Appendix

In this section, the following documents are presented:

Appendix 1: Market indicators (related to chapter one, Introduction)

Appendix 2: Box plots for excess return series (related to chapter four, Methodology)

Appendix 3: Dot plots for excess returns series (related to chapter four, Methodology)

Appendix 4: BDS test for pure random walk as DGP (related to chapter six, Data Generating Process)

Appendix 5: BDS test for ARMA process as DGP (related to chapter six, Data Generating Process)

Appendix 6: ARMA-GARCH for entire period including dummy for Euro (related to chapter six, Data Generating Process)

Appendix 7: Information criteria and model selection (related to chapter five, Descriptive Statistics and Univariate Analysis, chapter six, Data Generating Process and chapter 7, Multivariate Analysis).

10.1 Appendix 1: Market indicators

Data were retrieved from World Federation of Exchanges.

Market Capitalisation in USD Millions

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
NYSE Euronext (US)	11,534,61	11,026,586	9,015,270	11,328,953	12,707,578	13,632,303	15,421,167	15,650,832	9,208,934	11,837,793	13,394,081
NYSE Euronext (Europe)	2,271,727	1,889,455	1,538,684	2,076,410	2,441,261	2,706,803	3,712,680	4,222,679	2,101,745	2,869,393	2,930,072
London SE /London SE Group	2,612,230	2,164,716	1,856,194	2,460,064	2,865,243	3,058,182	3,794,310	3,851,705	1,868,153	3,453,622	3,613,064
Deutsche Börse	1,270,243	1,071,748	686,013	1,079,026	1,194,516	1,221,106	1,637,609	2,105,197	1,110,579	1,292,355	1,429,719

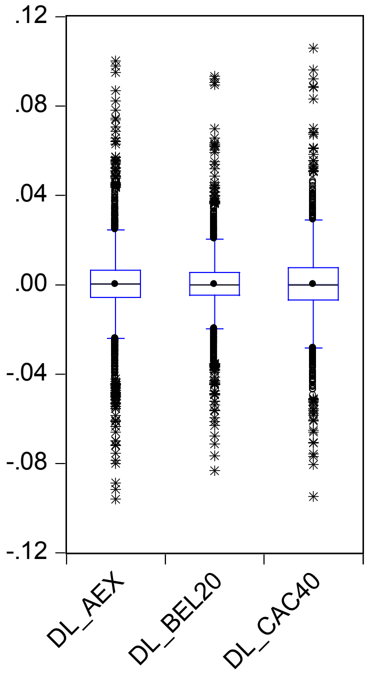
Total Number of listed companies

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
NYSE Euronext (US)	2,468	2,400	2,366	2,308	2,293	2,270	2,280	2,297	1,963	2,327	2,238
NYSE Euronext (Europe)	1,216	1,195	1,114	1,392	1,333	1,259	1,210	1,155	1,238	1,160	1,135
London SE /London SE Group	2,374	2,332	2,824	2,692	2,837	3,091	3,256	3,307	3,096	3,088	2,966
Deutsche Börse	983	983	934	866	819	764	760	866	832	783	765

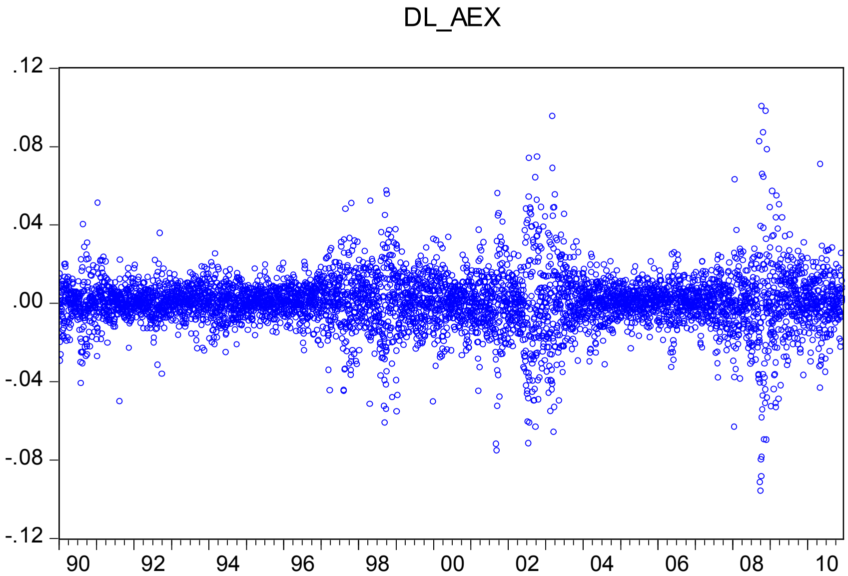
Share Trading in USD Millions

	2001	2002	2003	2004	2005	2006	2007	2008
NYSE Euronext (US)	10,489,030	10,310,055	9,691,335	11,618,150	14,125,292	21,789,470	29,113,786	33,638,937
NYSE Euronext (Europe)	2,092,540	1,974,133	1,936,573	2,472,131	2,906,208	3,853,321	5,639,760	4,476,711
London SE /London SE Group	4,520,183	4,001,339	3,609,718	5,169,023	5,677,721	7,571,698	10,333,685	6,271,520
Deutsche Börse	1,423,370	1,212,301	1,299,327	1,541,122	1,915,304	2,737,195	4,324,928	4,696,702

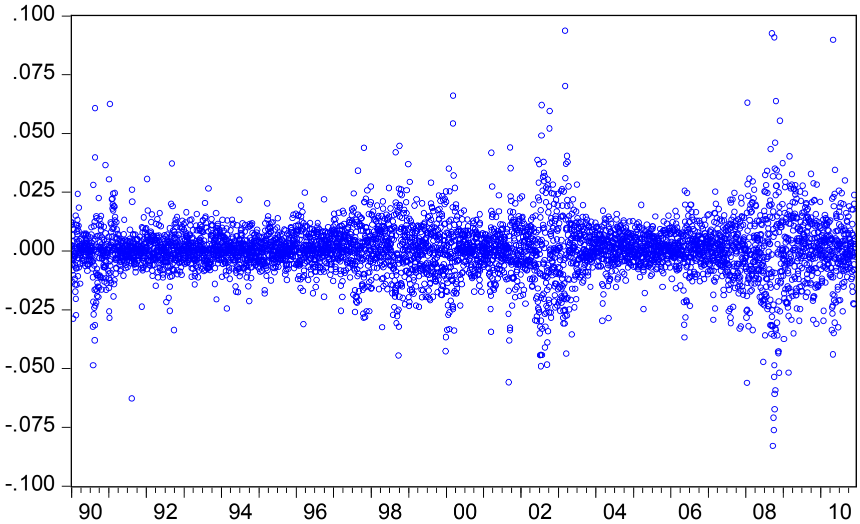
10.2 Appendix 2: Box plots for excess returns



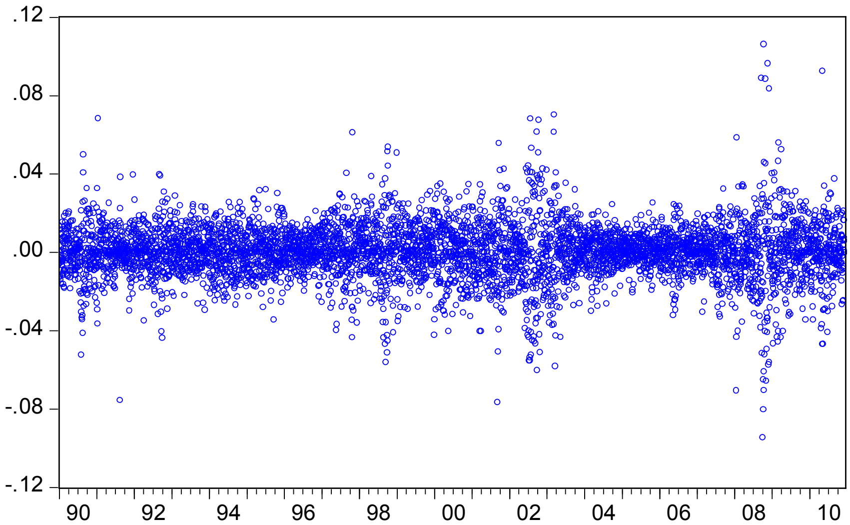
10.3 Appendix 3: Dot plots for excess returns



DL_BEL20



DL_CAC40



10.4 Appendix 4: BDS test for pure random walk as DGP

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
Entire period						
BDS m=2*	0.026921 (0.001339)	0.026850 (0.001339)	0.0.5862 (0.001363)	0.035806 (0.001362)	0.014044 (0.001201)	0.013968 (0.001201)
BDS m=3*	0.056490 (0.002131)	0.056356 (0.002130)	0.067909 (0.002163)	0.067784 (0.002161)	0.030971 (0.001904)	0.030841 (0.001903)
BDS m=4*	0.079960 (0.002541)	0.079780 (0.002540)	0.092883 (0.002572)	0.092703 (0.002570)	0.044970 (0.002260)	0.044803 (0.002259)
BDS M=5*	0.095200 (0.002652)	0.094998 (0.002651)	0.108650 (0.002678)	0.108413 (0.002675)	0.053179 (0.002349)	0.052987 (0.002348)
Pre-integration period						
BDS m=2*	0.022881 (0.001755)	0.022811 (0.001754)	0.029018 (0.001835)	0.028943 (0.001832)	0.008587 (0.001527)	0.008539 (0.001526)
BDS m=3*	0.046388 (0.002788)	0.046265 (0.002785)	0.053536 (0.002915)	0.053359 (0.002910)	0.016428 (0.002418)	0.016416 (0.002417)
BDS m=4*	0.062740 (0.003318)	0.062557 (0.003315)	0.072503 (0.003469)	0.072280 (0.003464)	0.022740 (0.002869)	0.022704 (0.002867)
BDS M=5*	0.073937 (0.003457)	0.073686 (0.003454)	0.083522 (0.003614)	0.083255 (0.003609)	0.06288 (0.002980)	0.026274 (0.002977)
Integration period						
BDS m=2*	0.027694 (0.004208)	0.027628 (0.004210)	0.037799 (0.004439)	0.037761 (0.004439)	0.011566 (0.003625)	0.011573 (0.003625)
BDS m=3*	0.064507 (0.006709)	0.064454 (0.006711)	0.077397 (0.007071)	0.077388 (0.007071)	0.030762 (0.005751)	0.030864 (0.005752)
BDS m=4*	0.103429 (0.008018)	0.103440 (0.008018)	0.113304 (0.008442)	0.113345 (0.008441)	0.051817 (0.006838)	0.051942 (0.006840)
BDS M=5*	0.132260 (0.008387)	0.132337 (0.008387)	0.141255 (0.008823)	0.141315 (0.008822)	0.067187 (0.007116)	0.067328 (0.007119)
Post-integration period						
BDS m=2*	0.015488 (0.002068)	0.021516 (0.002186)	0.034778 (0.002139)	0.034425 (0.002149)	0.016293 (0.002055)	0.016238 (0.002056)
BDS m=3*	0.038194 (0.003280)	0.48567 (0.003477)	0.068638 (0.003402)	0.068348 (0.003416)	0.038142 (0.003263)	0.038076 (0.003263)
BDS m=4*	0.058461 (0.003898)	0.072939 (0.004145)	0.096266 (0.004053)	0.096135 (0.004070)	0.057601 (0.003883)	0.057534 (0.003883)
BDS M=5*	0.070545 (0.004056)	0.088872 (0.004326)	0.114307 (0.004228)	0.114194 (0.004245)	0.071005 (0.004044)	0.070924 (0.004044)

BDS Statistics (Standard error in parenthesis). All estimates are significant at 1%.

10.5 Appendix 5: BDS test for ARMA process as DGP

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
Entire period						
BDS m=2*	0.026887 (0.001343)	0.026826 (0.001343)	0.035861 (0.001363)	0.035805 (0.001362)	0.014184 (0.001196)	0.014131 (0.001195)
BDS m=3*	0.056696 (0.002137)	0.056573 (0.002136)	0.067907 (0.002163)	0.067783 (0.002161)	0.030797 (0.001895)	0.030698 (0.001894)
BDS m=4*	0.080108 (0.002548)	0.079964 (0.002547)	0.092880 0.002572)	0.92702 (0.002675)	0.044634 (0.002251)	0.044494 (0.002249)
BDS M=5*	0.095201 (0.002659)	0.095055 (0.002658)	0.108647 (0.002678)	0.108411 (0.002675)	0.052755 (0.002339)	0.052591 (0.002338)
Pre-integration period						
BDS m=2*	0.022325 (0.001756)	0.022256 (0.001755)	0.022256 (0.001755)	0.028947 (0.001832)	0.088613 (0.001527)	0.008569 (0.001526)
BDS m=3*	0.045605 (0.002789)	0.045460 (0.002786)	0.045460 (0.002786)	0.053363 (0.002910)	0.016361 (0.0022668)	0.016355 (0.002416)
BDS m=4*	0.061717 (0.003320)	0.061502 (0.003316)	0.061502 (0.003316)	0.072284 (0.003464)	0.022668 (0.002869)	0.088636 (0.002867)
BDS M=5*	0.072879 (0.003458)	0.072637 (0.003454)	0.072637 (0.003454)	0.083258 (0.003609)	0.026192 (0.002980)	0.026177 (0.002977)
Integration period						
BDS m=2*	0.027018 (0.004141)	0.027024 (0.004141)	0.037749 (0.004439)	0.037773 (0.004440)	0.011362 (0.003569)	0.011292 (0.003569)
BDS m=3*	0.62820 (0.006598)	0.062894 (0.006597)	0.077366 (0.007070)	0.077334 (0.007071)	0.029780 (0.005682)	0.029672 (0.005682)
BDS m=4*	0.101257 (0.007879)	0.101317 (0.007877)	0.113241 (0.008441)	0.113182 (0.008443)	0.050874 (0.006776)	0.050821 (0.006780)
BDS M=5*	0.130200 (0.008237)	0.130295 (0.008233)	0.141183 (0.008822)	0.141157 (0.008824)	0.066521 (0.007078)	0.066492 (0.007080)
Post-integration period						
BDS m=2*	0.021599 (0.002181)	0.021516 (0.002186)	0.033886 (0.002151)	0.033914 (0.002151)	0.016121 (0.002057)	0.016093 (0.002058)
BDS m=3*	0.048863 (0.003468)	0.48567 (0.003477)	0.067575 (0.003420)	0.067611 (0.003420)	0.038991 (0.003265)	0.038949 (0.003265)
BDS m=4*	0.073468 (0.004133)	0.072939 (0.004145)	0.095472 (0.004076)	0.095523 (0.004076)	0.059074 (0.003883)	0.059032 (0.003884)
BDS M=5*	0.089321 (0.004312)	0.088872 (0.004326)	0.113676 (0.004252)	0.113717 (0.004251)	0.072678 (0.004042)	0.072615 (0.004043)

BDS Statistics (Standard error in parenthesis). All estimates are significant at 1%.

10.6 Appendix 6: ARMA-GARCH for entire period including dummy for Euro

Variable	AEX log-return	AEX excess return	BEL20 log-return	BEL20 excess return	CAC40 log-return	CAC40 excess return
c_0	0.000692*** (0.000154)	0.000468*** (0.000154)	0.000202 (0.000133)	-0.000035 (0.000134)	0.000306 (0.000205)	-0.00005 (0.000205)
Dummy	-0.000148 (0.000229)	-0.0000268 (0.000230)	0.000271 (0.000199)	0.000396** (0.000200)	0.000254 (0.000272)	0.000403 (0.000272)
c_1	-0.017118 (0.013175)	-0.016646 (0.013175))	0.060924*** (0.013765)	0.062272*** (0.013762)	-0.037604*** (0.013594)	-0.037182*** (0.013598)
a_1	-0.011845 (0.009742)	-0.011846 (0.009763)	0.060075*** (0.022290)	0.059700*** (0.022219)	-0.057980*** (0.015702)	-0.058163*** (0.015685)
b_1	-0.901715*** (0.093644)	-0.901228*** (0.0945241)	-0.520214** (0.217974)	-0.522217** (0.218110)	0.174114 (0.335423)	0.167698 (0.335428)
a_0	0.000149*** (0.0000513)	0.000149*** (0.0000514)	0.000128*** (0.0000481)	0.000128*** (0.0000476)	0.000220*** (0.000047)	0.000220*** (0.000047)
p	0.990483*** (0.004158)	0.990518*** (0.004145)	0.986251*** (0.006154)	0.986226*** (0.006130)	0.984700*** (0.004879)	0.984724*** (0.004871)
φ	0.093624*** (0.007979)	0.093310*** (0.007954)	0.127280*** (0.012171)	0.122888*** (0.021227)	0.090948*** (0.008842)	0.090760*** (0.008830)
Dummy	0.0000003 (0.0000003)	0.0000005 0.0000006	0.0000007** (0.0000003)	0.0000007** (0.0000003)	-0.0000005 (0.0000004)	-0.0000005 (0.0000004)

* significance at 10%, ** significance at 5%, *** significance at 1%

10.7 Appendix 7: Information criteria and model selection

Information criteria are measurements that can be used to choose among competing models. The most basic criterion that can be used to select a model is the coefficient of determination,R^2, which is given by the ratio of the explained sum of squares to the total sum of squares:

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS} \qquad (10.1)$$

The value of the coefficient lies between 0 and 1, and the closer it is to 1, the better is the fit. There is however some problems related to this measurement of goodness of fit, the most important being that R^2cannot fall when more variables are added to the model: "of course, adding more variables to the model may increase R^2 but it may also increase the variance of forecast error" (Gujarati, 2003, p. 537).

Hence, information criteria including a penalty factor for adding extra variables should be used when selecting a model. Two popular measurements are the Akaike Information Criteria (AIC) and the Schwarz Bayesian Information Criteria (BIC).

The AIC is given by the following equation:

$$AIC = e^{2k/n}\frac{\sum \hat{u}^2}{n} = e^{2k/n}\frac{RSS}{n} \quad (10.2)$$

where k is the number of regressors (including the intercept), n is the number of observations. For convenience, the equation is converted in logarithm:

$$\ln AIC = \left(\frac{2k}{n}\right) + \ln\left(\frac{RSS}{n}\right) \quad (10.3)$$

where $\ln AIC$ is the natural log of AIC, $[2k/n]$ is the penalty factor. In comparing two models, the lowest value of AIC is preferred.

The BIC is defined as:

$$BIC = n^{k/n}\frac{\sum \hat{u}^2}{n} = n^{k/n}\frac{RSS}{n} \quad (10.4)$$

The log-form is given by:

$$\ln BIC = \frac{k}{n}\ln n + \ln\left(\frac{RSS}{n}\right) \quad (10.5)$$

where the expression $\left[\left(\frac{k}{n}\right)\ln n\right]$ is the penalty factor. As for the AIC, the model with the lowest value of BIC is preferred.

The two information criteria are therefore similar in the sense that they prefer a model that will minimize the residual sum of squares, $\left[\ln\left(\frac{RSS}{n}\right)\right]$. However, the penalty factor for adding extra variable to the model imposed by the BIC, $\left[\left(\frac{k}{n}\right)\ln n\right]$, is harsher than the penalty factor for AIC, $[2k/n]$. Hence the BIC should help choosing the most parsimonious model. In this thesis, the BIC is adopted.

In EVIEWS7, the BIC is computed as:

$$\ln BIC = -2\left({}^{l}/_{T}\right) + {}^{k}/_{T} \ln T \qquad (10.6)$$

where l is the log of the likelihood function, k is the number of parameters estimated and T is the number of observations.