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VOLATILITY TRANSMISSION BETWEEN INTERNATIONAL STOCK MARKETS

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INTRODUCTION

The world's economic and financial systems are becoming increasingly linked due to the rapid expansion of international trade caused by different processes of market liberalization and political integration. Indeed, an important outcome of globalization is increased comovement in asset prices across markets. This comovement, of course, also stimulates vulnerability to market shocks. Thus, shocks originated in one market are transmitted to other financial markets. Some argue that these linkages could even be destroying the very benefits that diversification offered in the first place. This dissertation contributes to the discussion on how to measure and analyze all these issues.

The study of comovements between stock market returns is at the heart of finance and has recently received much interest in a variety of literatures, especially in international finance. But what are the key forces driving this comovement? Traditional asset pricing models (such as the CAPM and its multifactor variants) and most of the studies analyzing international linkages between financial markets offer little hint, because they have mainly focused on the analysis of first moments. Thus, a significant number of researchers have evaluated correlations and cointegration structure of international equity markets. It was not until the 90s that academics started to realize the importance of modeling, as well, interactions in second moments. In fact, it seems that some markets have even more interdependence in volatility than in returns.

The importance of understanding volatility transmission mechanisms comes from their determinant consequences on monetary policy, optimal resources allocation, risk measurement, capital requirements and asset valuation. From an investor's point of view, a better understanding of how markets move together may result in superior portfolio construction and hedging strategies, while regulators may mainly be interested in the actual causes and consequences of such spillovers.

There is a very close connection between the terms integration and diversification. As financial markets are becoming increasingly integrated, there is a higher need to carefully monitor the varying benefits of diversification. A well known result in finance is that the lower the covariance between portfolio assets, the smaller the variance of a diversified portfolio. Therefore, the primary aim of diversification is to take advantage of the low correlations between stocks. No matter if the investor strategy is applied at the industry, national or international level. One of our objectives will be to analyze which level generates the greater risk diversification.

While there is considerable agreement that globalization and integration move together in the same direction, there is not a clear opinion on whether further integration should increase or decrease volatility transmission between financial markets. Our main hypothesis is that further globalization and integration will also increase interrelations in second moments. As a country becomes more integrated into world capital markets, more of its variance might be explained by changes in common world factors (and less by local factors).

Therefore, the aim of the four chapters in this dissertation is to increase the understanding of the interrelations between international stock markets. In order to do so, in Chapter 1 we analyze the different econometric methodologies available to model these dynamics. The remaining three chapters use multivariate conditional volatility models and link them to the analysis of volatility transmission (Chapter 2), diversification (Chapter 3) and integration (Chapter 4).

Chapter 1, entitled "VOLATILITY TRANSMISSION MODELS: A SURVEY", reviews the literature on volatility transmission in order to determine what we have learnt about the different methodologies applied and which questions are yet to be answered. As far as we know, no other study reviews volatility transmission in such a broad manner. In particular, GARCH, regime switching and stochastic volatility models are analyzed. In addition, this chapter covers several concrete aspects such as their scope of application, the overlapping problem, the concept of efficiency and asymmetry modeling. Finally, emerging topics and unanswered questions are identified, serving as an agenda for future research. Thus, the main objective of this chapter is to offer a broad vision of the *state of the art* in volatility transmission models and, at the same time, motivate further research.

Chapter 2 is entitled “VOLATILITY TRANSMISSION PATTERNS AND TERRORIST ATTACKS”. The main objective of this study is to analyze how volatility transmission patterns are affected by stock market crises. Thus, we analyze volatility transmission between the US and Eurozone stock markets considering the effects of the September 11, 2001, March 11, 2004 and July 7, 2005 financial crises. In order to do this, we use a multivariate GARCH model and consider both the asymmetric volatility phenomenon and the non-synchronous trading problem. The data consists of simultaneous daily stock market prices recorded at 15:00 GMT time for the period 2000 to 2006. This study innovates with respect the existing literature in two ways. First, as far as we know, these terrorist attacks have not yet been included in any paper analyzing volatility transmission in international markets. Second, we introduce a new version of Asymmetric Volatility Impulse Response Functions (AVIRF) which takes into account stock market crises. Results suggest that there is bidirectional and asymmetric volatility transmission and show the different impact that terrorist attacks had on both markets.

Chapter 3, entitled “REGION VERSUS INDUSTRY EFFECTS AND VOLATILITY TRANSMISSION”, has two main objectives. First, it analyzes the relative importance of regional versus industrial effects in stock returns (as opposed to the extensively analyzed country versus industrial effects), using a sample including the period after the bursting of the TMT bubble. Second, it analyzes volatility transmission patterns within an industry across regions, in order to assess whether the same international linkages found in aggregate stock market indices exist at the industry level. The data set consists of daily price from 1995 to 2004 for 10 industry indices in 3 different regions (North America, European Union and Asia). We seek to contribute to the existing literature in several ways. Firstly, to our knowledge, this study is the first one to focus on specific regions rather than countries. Secondly, it analyzes volatility transmission, through multivariate GARCH models, using industrial indices. Thirdly, another important difference to other studies is the use of daily data. The vast majority of empirical studies use weekly and monthly data, though portfolio managers are surely interested in the behavior of daily returns. Finally, this study uses a wide sample that includes the bursting of the TMT bubble. The results confirm the overall dominance of regional effects over industry effects, except for the TMT bubble period. In the volatility transmission analysis, the results are suggestive of spillovers, more or less important depending on the industry being analyzed.

We find that region factors are more important than industry factors in explaining the benefits of international diversification. However, these findings do not identify the origin of these independent country/region movements. The greater diversification benefits for countries/regions could be the result of independent variation of country/region specific *discount rates*, resulting from segmented capital markets. Alternatively, this could result from a lack of integration in trade flows or industry specialization, leading to country/region specific innovations in expected *cash flows*.

Chapter 4 is entitled "GLOBAL VERSUS REGIONAL AND ECONOMIC VERSUS FINANCIAL INTEGRATION IN EUROPEAN STOCK MARKETS". This chapter links the concepts of shock transmission and integration. Therefore, in order to measure global and regional integration we look at shock spillover intensities and proportions of variance explained by US and EU shocks for 21 local European countries, over the period 1973-2005. In general, shock spillover intensity has increased in time, suggesting a higher degree of both global and regional integration. Regarding proportions of variance, both the US and European markets have gained considerably in importance for individual European financial markets, though Europe has not taken over from the US as the dominant market in Europe.

This time, we also analyze the underlying drivers of return variation to determine whether the benefits of international diversification are being driven by the degree of integration in goods (economic integration) or financial markets (financial integration). Thus, the main goal of this chapter is to investigate to what extent the increased exposure of 21 local European equity markets with respect to US market shocks is the result of a convergence in cash flows or a convergence in discount rates. The former would be consistent with globalization and further economic integration, the latter with further financial integration. Therefore, the main innovation of this study is to look at exposures to cash-flow and discount-rate shocks as measures of economic and financial integration. In a first step, we decompose monthly US equity market returns into a component due to revisions in future cash flows (cash-flow news) and a component due to revisions in future discount rates (discount-rate news), using a VAR framework. Second, we confirm that betas of local European equity markets with respect to the US market have increased substantially over time. We find that this increase is nearly fully the consequence of an increase in the discount-rate beta. We see this as evidence that the increased correlation of European equity markets with global equity markets is the result of improved financial integration, and to a much lesser extent economic integration.

Finally, we present an overview of the main contributions and results of this dissertation.

CHAPTER 1

Volatility Transmission Models: A Survey

1.1 Introduction

During the last decades, we have seen how different financial crises, originated in particular regions or countries, have extended geographically. In fact, the interrelation among different countries has been a topic extensively analyzed by academics and professionals for a long time. As far as international markets are becoming more and more integrated, information generated in one country can, without any doubt, affect other markets. Although the methodologies analyzed in this survey have been mostly applied to the analysis of common movements in international financial markets, this study extends their scope of application to other financial markets and assets.

First of all, the concepts of *interdependency* and *contagion* should be differentiated. The first term is much wider and includes all types of interrelations, both in mean and in variance, that may exist between two assets or markets. Regarding the concept of contagion, it seems that the literature has not reached an agreement for a common definition. This study uses the most restrictive definition, the one that has been historically mostly used, that defines contagion as an increase in cross-correlations after a crisis or shock. Without any doubt, the importance of understanding volatility transmission mechanisms comes from their determinant consequences on monetary policy, optimal resources allocation, risk measurement, capital requirements and asset valuation.

Since the pioneer studies in international transmission of shocks in returns such as Eun and Shim (1989), most of the empirical studies have focused on the analysis of relations in mean among different markets. It was in the 90s when academics started to realize the importance of modeling, as well, interactions in second moments. This way, studies on volatility transmission between monetary markets (Engle *et al.* (1990a)), where extended to international stock markets (Hamao *et al*. (1990), Koutmos and Booth (1995) or Booth *et al*. (1997), among others). In fact, it seems that some markets have even more interdependence in volatility than in returns. This survey will try to focus on volatility transmission, although it will inevitably include the rest of interactions.

Given the diversity of the existing literature, this study pretends to order ideas in an easy structure that will enable the reader to have a broad but reliable vision of the investigation in this field. Six main methodologies have been used in the literature to analyze interrelations between financial markets: cross-correlations, VAR models, Cointegration models, GARCH models, Regime Switching models and Stochastic Volatility models. This study proposes to analyze the last three approaches, those particularly focused on volatility transmission.

This study reviews the literature on volatility transmission in order to determine what we have learnt about the different methodologies applied and which questions are yet to be answered. As far as we know, no other study reviews volatility transmission in such a broad manner. There exist excellent surveys on specific methodologies, but none of them covers all of them or their scope of application. Thus, Claessens and Forbes (2001) focus on the concept of *contagion*. Bollerslev *et al*. (1992), Bera and Higgins (1993), Bollerslev *et al*. (1994), Engle (1995) and Gourieroux (1997) among others, stand out for surveys on GARCH modeling. Bauwens *et al*. (2006) present a more recent study for the multivariate case. Similarly, Ghysels *et al*. (1996), Shephard (2005) and Asai *et al*. (2006) offer complete revisions on Stochastic Volatility models. Finally, Poon and Granger (2003) offer a survey on different methodologies for volatility forecast. This survey differs from the others in several aspects. First, it focuses on distinguishing applicable methodologies as such, without focusing on their application to concrete markets. Second, the main objective is to offer a broad vision of the *state of the art* to the non-expert and, at the same time, motivate further research. Therefore, without giving too specific empirical results by regions or markets, it tries to become a guide for those researchers that wish to deepen in this matter. In this sense, it should be highlighted that this survey is intended to give a general vision of the available methodologies and it is not its purpose to cover all existing theoretical and empirical studies.

The structure of the study is as follows. Section 2 analyzes different methodologies applied in the analysis of volatility transmission. Section 3 focuses on different aspects related to the application of these methodologies, concretely: financial markets, overlapping problems, efficiency and asymmetries. Section 4 offers general methodological proposals and identifies key issues for future research. In Section 5, the main conclusions are presented. Finally, Tables 1 and 2 offer a synthesis of the main empirical studies reviewed.

1.2 Methodologies

In this section, we review the different methodologies that have been applied in the literature to the analysis of volatility transmission. We propose to classify methodologies into three categories: 1) GARCH models, 2) Regime Switching models and 3) Stochastic Volatility models.

1.2.1 GARCH

Since the concept of conditional heteroskedasticity was introduced in Engle (1982), numerous studies have applied and extended this methodology. In concrete, the extension to *Generalized Autoregressive Conditional Heteroskedasticity* (GARCH) models proposed by Bollerslev (1986) has been extensively applied in studies analyzing relations between financial markets. This methodology allows to differentiate the effects described by Engle *et al*. (1990b) as *heat waves* and *meteor showers*. The hypothesis of heat waves is consistent with the idea that most of the volatility sources are country specific. On the contrary, the meteor shower hypothesis is consistent with the idea of shock transmission between different markets, countries or regions. In a multivariate GARCH estimation, the relative importance of own and cross coefficients allows to differentiate the existence or not of such effects.

In this section, we will analyze some of the specifications most commonly used to analyze short term interdependencies, both in the case of univariate and multivariate GARCH models.

1.2.1.1 Estimation in two stages: univariate GARCH

Hamao *et al*. (1990) was the first study that applied the univariate GARCH methodology to analyze relations between international markets. In this study, they analyze daily volatility transmission among the New York, London and Tokyo stock markets using a two stages approach. Firstly, MA(1)-GARCH(1,1) models are estimated for each one of the markets individually and, secondly, the squared residuals of the previous estimated models are used as regressors in the variance equation of the other markets. Thus, one can determine if there exists a relation between the domestic market variance and the "volatility surprise" of the foreign market. In particular, they find volatility spillovers from New York to London and Tokyo and from London to Tokyo, being the corresponding coefficients significant and positive.

Other studies that have used univariate GARCH specifications in two stages to analyze volatility transmission between financial markets are Engle *et al.* (1990b), Peña (1992) or Wang *et al*. (2002). All of them find evidence supporting the meteor shower hypothesis in their respective markets and only Susmel and Engle (1994) find more important the heat wave effect. In this sense, Ito *et al*. (1992) propose a variance decomposition method to determine which proportion corresponds to meteor shower effects and which to heat wave effects, finding in their analysis on exchange rates bigger the first one. Following with their analysis, they suggest that the meteor shower effect is due to gradual dissemination of private information and not to policy coordination.

The specification of the mean equation as a moving average (MA) process is also a constant in the literature reviewed and it tries to model the autocorrelation observed in most of the financial series analyzed. Generally, it is introduced in the case of stock market indexes because, as suggested by Scholes and Williams (1977), the lack of synchronization of individual stocks and bid-ask spreads produce serial correlation.

A GARCH in mean model (GARCH-M), used among others by Susmel and Engle (1994), Lin *et al*. (1994), Kim and Rogers (1995), Hsin (2004) and Kim (2005), allows the researcher to analyze the relation between returns and volatility.

A lot of studies include in their specifications dummy variables, both in the mean and variance equations, in order to model day of the week effects, holiday effects, crises, periods of extremely high volatility or asymmetries. Susmel and Engle (1994), among others, do not find evidence for weekend effects and this is coherent with the observation made by Connolly (1989) that there is few evidence of such an effect when heteroskedasticity is taken into account. Furthermore, a lot of studies also include as regressors in their equations macroeconomic variables that help them obtain better specifications. For instance, Hsin (2004) finds that the returns of a global index and the dollar exchange rate are relevant variables. Also in this sense, Wongswan (2006) analyzes the effect of foreign countries macroeconomic announcements over conditional variance and trade volume.

Several studies highlight the relevance of the variable *trade volume* as explicative variable for the conditional variance (see Peña (1992), Pyun *et al*. (2000) and Kim (2005), among others). They suggest that its introduction can reduce persistency in volatility or, what is the same, that it can be an important source of conditional heteroskedasticity.

Aggarwal *et al*. (1999) use a model that combines a GARCH specification with changes of regime. In particular, they use the *iterated cumulative sums of square* (ICSS) algorithm of Inclan and Tiao (1994) to determine points of change in volatility and examine global and local events that took place in that moment. These changes are then introduced as dummies in the variance equation of the GARCH model, which is estimated by Quasi-Maximum Likelihood (QML). In their study on emerging markets they found that most of the volatility changes where due to local factors, being the 1987 crash the only global factor found in their sample covering from 1985 to 1995. GARCH coefficients are reduced or even become non-significant when changes of regime are introduced.

Susmel (2000) analyzes as well the possibility of introducing changes of regime, but using an E-SWARCH specification, that also includes asymmetries. Both ARCH and asymmetric effects are reduced when changes of regime are introduced. Its strategy consists of determining the different regimes or states in the analyzed countries and comparing them. It finds common volatility states in Canada and US on one hand and Japan and UK on the other.

One of the main features of several financial time series that is not properly modeled by standard GARCH specifications is the asymmetry or leverage effect. This concept has its origin in the works of Black (1976), French *et al*. (1987), Schwert

(1990) and Nelson (1991). An unexpected fall in returns tends to increase volatility more than an unexpected rise of the same magnitude. Several univariate specifications can model this effect, being the most outstanding those of Nelson (1991) (EGARCH), Glosten, Jagannathan and Runkle (1993) (GJR-GARCH) and Zakoian (1994) (T-GARCH). Ding *et al*. (1993) propose a general model that includes several asymmetric specifications, the APARCH. The most commonly used specifications in the univariate analysis of volatility transmission among financial markets have been the GJR model, that introduces asymmetries by means of dummy variables (see Bae and Karolyi (1994), Illueca and Lafuente (2002) or Wang *et al*. (2002)), and the EGARCH model (see Kim (2005) and Lee *et al*. (2004)). Other specifications commonly used in the empirical literature are the PNP-GARCH used by Bae and Karolyi (*op.cit.*) or the T-GARCH used by Hsin (2004) and Lafuente and Ruiz (2004), among others. Several studies that model asymmetries such as Susmel and Engle (1994) or Bae and Karolyi (*op.cit.*) suggest that studies that do not take them into account could reach incorrect conclusions.

The Aggregate-Shock (AS) and Signal-Extraction (SE) models are special cases of the application of univariate GARCH models in two stages to analyze international volatility transmission (see Lin *et al*. (1994)). They are used, among others, by King and Wadhwani (1990), Jimeno (1995) and Hsin (2004). They present two different ways of modeling how domestic investors process international information. The AS model uses as explicative variables for domestic overnight returns, the daily return and the unexpected return in the foreign market (e_t). The SE model decomposes e_t into uncorrelated shocks: global and local. In the case of the AS model estimated in two stages, Lin *et al*. (1994) suggest that it is equivalent to a multivariate process when mean equations are correctly specified and there is no correlation between daily and overnight domestic returns. However, this statement is easily criticizable due to the exigency of the assumptions and the benefits of the multivariate estimation.

Cheung and Ng (1996) develop a useful test for causality in variance. The test is based on the residual cross-correlation function (CCF), obtained from the estimation of univariate GARCH models. Similarly, Pascual-Fuster (2000) analyzes volatility transmission between a stock quoted in different non-overlapping markets. He proposes to estimate univariate GARCH models for the individual series and, once conditional variances have been obtained, to estimate correlations between those variances.

Finally, among the empirical literature using GARCH methodology, there exist several studies that, based on the *world factor model* of Bekaert and Harvey (1997), analyze the influence of global, regional and local factors on domestic volatilities (see Aggarwal *et al*. (1999), Ng (2000), Hsin (2004) or Batra (2004), among others). Similarly, Illueca and Lafuente (2002) analyze the factor structure of stock market return and volatility from a representative set of international stock exchanges. They find that the propagative price causal transmission among international stock markets is more intense in terms of volatility.

1.2.1.2 Joint estimation: multivariate GARCH

As it has been shown, studies using univariate models normally introduce an estimation of the conditional variance of series X as explicative variable in the conditional variance of series Y, or vice versa. However, this univariate estimation ignores the possibility of having causality between volatilities in both directions and does not exploit the covariance between both series. A more effective way of estimating interactions among volatilities of N different time series is to estimate a multivariate GARCH model. In this case, variances and covariances of the N series are simultaneously estimated, generally using Maximum Likelihood (ML). Engle *et al*. (1984) was the first study to introduce a bivariate ARCH model. However, it was the study by Engle and Kroner (1995), based on a previous working paper by Baba *et al*. (1990), that introduced a rigorous analysis of the theoretical properties of multivariate GARCH models.

A multivariate GARCH model should not be estimated without previously checking the existence of such an effect in the series. For this reason, GARCH specification tests must be used *a priori*. Moreover, Kim and Rogers (1995) suggest analyzing cross-correlations of squared returns, as this will give a first idea of the existence or not of interrelations in the series second moments. In many cases, this cross-correlation is even bigger than in levels.

Now, some of the multivariate GARCH representations most used in the literature will be presented. Let y_t be a vector with dimension ($Nx1$). The conditional mean of y_t is also a vector with dimension (*Nx1*) that we will denote as μ_t and the conditional variance for y_t is a (*NxN*) matrix, represented by H_t. The diagonal elements of H_t are variance terms and elements outside the diagonal are covariances. There exist several representations of multivariate GARCH models, being the most commonly used the VECH, Diagonal, BEKK and CCC representations. Moreover, there exist other extensions such as the multivariate GARCH in mean (GARCH-M), Factor ARCH (FARCH) and the multiple asymmetric multivariate GARCH versions. The main problem shared by multivariate GARCH models is the great number of parameters to be estimated. This should not be a problem, in theory, if there was a sufficiently large sample size. However, the efficient estimation of these models is done by Maximum Likelihood and it is difficult, in many cases, to obtain the convergence of the optimization algorithms involved in the process. Furthermore, restrictions must be imposed in the parameters of the model in order to guarantee the non-negativity of conditional variances in individual series. This implies to guarantee that H_t is positive definite and, in practice, this is not easy to accomplish.

The **VECH representation** (Bollerslev, Engle and Wooldridge (1988)) has the following specification:

$$vech(H_t) = vech(A_0) + \sum_{i=1}^{q} A_i vech(\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum_{i=1}^{p} B_i vech(H_{t-i}) \qquad (1)$$

where $\varepsilon_t = (\varepsilon_{1t},...,\varepsilon_{Nt})'$ are the error terms associated to mean equations from y_{1t} to y_{Nt} . A_0 is a positive definite matrix of parameters, A_i and B_i are parameters matrixes with size ($N(N+1)/2 \; x \; N(N+1)/2$) and the *vech* operator applied to a symmetric matrix puts the elements of the lower triangle in a column.

In the case of two variables ($N=2$) and p=q=1, the complete representation would be as follows:

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} a_{11}^0 \\ a_{12}^0 \\ a_{22}^0 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \qquad (2)$$

where $h_{11,t}$ is the conditional variance of y_{1t} 's corresponding error, $h_{22,t}$ is the conditional variance of y_{2t} 's corresponding error and $h_{12,t}$ is the conditional covariance between errors.

This specification implies a great number of parameters to be estimated (21 in the bivariate case) and certain restrictions must be accomplished in order to assure a positive definite H_t. Maybe due to this reason this specification has not been very popular in the empirical application of volatility transmission analysis.

In the **diagonal representation** (Bollerslev, Engle and Wooldridge (1988)), A_i and B_i are diagonal matrixes. This assumption makes individual conditional variances and covariances to have GARCH(p,q) form.

In the case of two variables ($N=2$) and $p=q=1$, the complete representation would be as follows:

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} a_{11}^0 \\ a_{12}^0 \\ a_{22}^0 \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \tag{3}$$

This representation beats the previous one in the sense of less parameters to be estimated. In the bivariate case, parameters are reduced from 21 in the VECH representation to 9 in the diagonal case. However, it assumes that individual conditional variances and covariances only depend on their own lags and lagged squared residuals. Therefore, important information such as interrelations between variances and covariances is lost. Furthermore, it is still necessary to impose restrictions in order to ensure a positive definite H_t.

De Santis and Gerard (1997), among few others, use this specification. In their case, they use monthly returns to test the conditional CAPM. In their sample, dependencies among different markets volatilities are not very strong and, for that reason, a diagonal representation is not that restrictive. Ledoit *et al*. (2003) develop an estimation procedure in the framework of the diagonal representation which is numerically feasible for large-scale problems.

The **BEKK representation** (Baba, Engle, Kraft and Kroner (1990) and Engle and Kroner (1995)) assumes the following model for H_t:

$$H_t = C_0^{'}C_0 + \sum_{i=1}^{q} A_i^{*'} \varepsilon_{t-i}\varepsilon_{t-i}^{'} A_i^{*} + \sum_{i=1}^{p} B_i^{*'} H_{t-i} B_i^{*} \tag{4}$$

where A_i^* and B_i^* are (NxN) parameter matrixes and C_0 is restricted to be upper triangular.

In the case of two variables ($N=2$) and $p=q=1$, the complete representation would be as follows:

$$\begin{aligned}\begin{bmatrix} h_{11,t} & h_{12,t} \\ \cdot & h_{22,t} \end{bmatrix} &= \begin{bmatrix} c_{11}^{0} & c_{12}^{0} \\ 0 & c_{22}^{0} \end{bmatrix}^{'} \begin{bmatrix} c_{11}^{0} & c_{12}^{0} \\ 0 & c_{22}^{0} \end{bmatrix} + \\ &\begin{bmatrix} a_{11}^{*} & a_{12}^{*} \\ a_{21}^{*} & a_{22}^{*} \end{bmatrix}^{'} \begin{bmatrix} \varepsilon_{1,t-1}^{2} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^{2} \end{bmatrix} \begin{bmatrix} a_{11}^{*} & a_{12}^{*} \\ a_{21}^{*} & a_{22}^{*} \end{bmatrix} + \\ &\begin{bmatrix} b_{11}^{*} & b_{12}^{*} \\ b_{21}^{*} & b_{22}^{*} \end{bmatrix}^{'} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11}^{*} & b_{12}^{*} \\ b_{21}^{*} & b_{22}^{*} \end{bmatrix}\end{aligned} \tag{5}$$

This specification improves VECH and diagonal representations because it practically assures that H_t will be positive definite. Furthermore, it does not require so many parameters to be estimated as in the VECH case (11 parameters in the bivariate case) and is more general than the diagonal representation as it allows certain relations that the last one would not allow, such as lagged variances influencing covariances. This is important when trying to test certain existing theories in the literature that intend to verify contagion relations or increases in common movements in high volatility states.

This representation has been the most popular in the literature. In fact, some studies such as Karolyi (1995) that propose and compare several specifications for the variances-covariances matrix conclude that this one is the most appropriate one among those analyzed.

Darbar and Deb (1997) apply this representation and, moreover, propose to decompose the estimated covariance in its permanent and transitory components. They find in their series evidence of significant transitory covariance and no null permanent covariance.

Kearney and Patton (2000) use a BEKK model in systems of three, four and five currencies from the European Monetary System, reaching different conclusions regarding movement transmission in each one of them. Therefore, before estimating a model, the proposed specification must be carefully analyzed. Movements in a BEKK model can be transmitted both directly through variances and indirectly through covariances.

As it occurred in the case of univariate estimations in two stages, multivariate estimation also allows asymmetries modeling and several studies have used these specifications. In particular, studies such as Brooks and Henry (2000) or Isakov and Pérignon (2001) propose a BEKK model with GJR asymmetry. Tai (2004) uses the same structure in a test of the conditional ICAPM (International Conditional Asset Pricing Model). The theoretical ICAPM model allows him to settle his contagion or volatility transmission analysis on a theoretical basis.

The **CCC representation** or Constant Conditional Correlation (Bollerslev (1990)) defines its conditional correlation matrix as follows:

$$R = \begin{bmatrix} 1 & \cdots & \rho_{1N} \\ \cdots & \cdots & \cdots \\ \rho_{N1} & \cdots & 1 \end{bmatrix} \tag{6}$$

where ρ_{ij} is the correlation coefficient between variables i and j. Then, it defines the conditional variance matrix H_t as:

$$H_t = diag\left(\sqrt{h_{11,t}},\cdots,\sqrt{h_{NN,t}}\right)Rdiag\left(\sqrt{h_{11,t}},\cdots,\sqrt{h_{NN,t}}\right) \tag{7}$$

where *diag* produces a diagonal matrix with the elements in (.) in the main diagonal.

In the case of two variables (*N=2*) and *p=q=1*, the complete representation would be as follows:

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \tag{8}$$

where individual variances $h_{11,t}$ and $h_{22,t}$ are univariate GARCH processes with *p=q=1*. In this specification, H_t is assured to be positive definite if certain restrictions on the parameters are fulfilled.

This representation has been very popular among empirical studies because it reduces the conditional correlation matrix to constant correlation coefficients between variables. Thus, the number of parameters to be estimated is small, if we compare it with other specifications (7 in the bivariate case). Some examples of studies using this specification are Longin and Solnik (1995), Karolyi (1995), Koutmos and Booth (1995), Koutmos (1996), Scheicher (2001), Bera and Kim (2002) or Baele (2005) for stock markets, Karolyi and Stulz (1996) for American Depositary Receipts (ADRs) and Bollerslev (1990) for exchange rates.

Simply, this model should only be applied when there is empirical evidence that correlation is constant in time. For instance, according to Bollerslev (1990), when constant conditional correlation is assumed, cross products of standardized residuals must be serially uncorrelated. Bollerslev (*op.cit.*), Longin and Solnik (1995), Tse (2000) and Bera and Kim (2002) propose different tests. Although Bera and Kim (2002)'s test is probably the most complete one, the rest have been used more often due to their relative easiness. However, in some studies such as Fong and Chng (2000), the validity of the assumption is not tested. Therefore, in our opinion, conclusions extracted from that analysis may be questionable. In studies made by Bollerslev (1990) for exchange rates and Scheicher (2001) for emerging stock markets indexes, the assumption is analyzed and verified. However, Longin and Solnik (1995), Bera and Kim (2002), Karolyi and Stulz (1996) and Sheedy (1998) suggest that neither stock market returns, nor ADRs, nor exchange rates can be properly modeled under this assumption. In the same way, Assoé (2001) finds the assumption inappropriate for stock market indexes and exchange rates in emerging markets. Longin and Solnik (1995) suggest and test three reasons why correlations should not be constant in time: a) trend existence, b) asymmetry and changes of regime in volatility and c) influence of macroeconomic variables. Therefore, they conclude that constant conditional correlation does not exist in stock markets. In the case of Karolyi and Stulz (1996), although correlations are not affected by macroeconomic announcements, shocks in interest rates nor shocks in exchange rates, correlations do increase when absolute returns are high. Alaganar and Bhar (2002) propose a bivariate GARCH model with constant conditional correlation but affected by external shocks through a dummy. Finally, Christodoulakis and Satchell (2002), Engle (2002) and Tse and Tsui (2002), among others, propose new multivariate GARCH models with time-varying correlations.

Most of the studies that propose a multivariate EGARCH specification (Braun *et al.* (1995)), assume as well constant conditional correlation (see Table 1). In these studies (see, for example, Booth *et al.* (1997), Niarchos *et al.* (1999) or Tse *et al.* (2003)), the appropriateness of the specification is verified using the Ljung-Box analysis on residuals, the constant correlation assumption test and the Engle and Ng (1993) test for asymmetry. Most of them, moreover, suggest a Student's t distribution for the residuals (see, for example, Booth *et al.* (1997) or Tse (1999)). However, according to Niarchos *et al.* (1999), this is only appropriate when the estimated degrees of freedom are higher than four.

The Factor ARCH model or **FARCH** from Engle, Ng and Rothschild (1990a) was also introduced to solve the problem of the high number of parameters to be estimated, keeping the benefits of a positive definite variances-covariances matrix. The model is defined by the following expression:

$$H_t = \sum_{k=1}^{K} \beta_k \beta_k^{'} \lambda_{kt} + \Omega \tag{9}$$

where Ω is a positive semidefinite matrix NxN, β_k are $Nx1$ linearly independent vectors and λ_{kt} are positive random variables. Furthermore, the mean equation is defined as follows:

$$y_t = \mu_t + \sum_{k=1}^{K} g_{kt} f_{kt} + v_t \tag{10}$$

where $E_{t-1}(f_{kt}) = 0$, $E_{t-1}(f_{kt} f_{jt}) = 0$, $E_{t-1}(v_t) = 0$ and $E_{t-1}(v_t v_t^{'}) = \Omega$. The f_{kt} are factors affecting returns in excess in all series, v_t is a vector of idiosyncratic noises and g_{kt} are time varying weight vectors.

This model has been used, among others, by Engle and Susmel (1993) and King *et al*. (1994). Studies using this model are normally completed with Engle and Kozicki (1993)'s test for common factors. Thus, for example, if two series with ARCH effects share a common factor, they may eliminate that effect with a linear combination of both series. This test has been used, for instance, by Arshanapalli *et al*. (1997) to provide evidence of the existence of a common intra-industrial global factor in stock market indexes returns. Other studies such as Booth *et al*. (1997), Niarchos *et al*. (1999) or Tse *et al*. (2003) do not find evidence of the existence of a common volatility factor in their respective markets.

With this kind of models, the existence of global common factors moving different markets can be analyzed. Although the most general model allows K factors and a time varying matrix Ω_t , Engle and Susmel (1993) work with one factor (a regional return) and $\Omega_t = \Omega$ in order to reduce the number of parameters to be estimated. Moreover, the common factor is supposed to follow a GARCH process. In King *et al*. (1994), the number of unobservable factors is two, and they include four observable factors. Thus, the variance proportion attributable to observable factors, unobservable factors and the idiosyncratic term, can be estimated. They find that volatility is determined by unobservable factors and, as Engle and Susmel (*op.cit.*) do, they suggest the existence of a common regional factor rather than a global one. These models can be interpreted as a dynamic version of the APT (*Arbitrage Pricing Theory*) models. As opposed to Engle and Susmel (*op.cit.*), King *et al*. (*op.cit.*) determine factors endogenously. They find that an increase in the volatility of those factors affecting all markets with the same sign (observable factors in their sample), is related to an increase in correlation between markets. On the other hand, increases in the volatility of those factors moving markets in opposite directions can be associated with a decrease in correlations coefficients.

There is an important disagreement in the literature concerning the existence of global or regional factors. Arshanapalli *et al*. (1997) suggest that some studies do not find common global factors because they use general stock market indexes with different industrial composition. As a result, the analysis is biased, and it is not possible to differentiate volatility sources coming from country effect from those coming from industry or sector effect. These multivariate studies try to differentiate local, regional and global shocks (see, for example, Scheicher (2001) or Miyakoshi (2003)).

The FARCH model can be estimated by Maximum Likelihood (ML) but, due to its high number of parameters, some computational problems may appear in its estimation. Engle *et al*. (1990a) suggest a two stages procedure in order to avoid this.

The main difference between FARCH and BEKK models in the number of factors affecting the conditional variances-covariances matrix. In the BEKK model there are N factors, as many as series or variables. In the FARCH model, there are $K<N$ factors. In a similar way, an alternative multivariate model, not included in the GARCH family but having similar characteristics to the FARCH, is the latent factor ARCH model of Diebold and Nerlove (1989). Fernández-Izquierdo and Lafuente (2004) also propose an alternative methodology to FARCH. Their approach is based on a two-stage procedure. First, they use a factor analysis technique to summarize the information contained in all stock exchanges into three latent factors. These factors can be associated to a specific international trading area. Then, they estimate a bivariate GJR-GARCH model for each pair of factors.

Kroner and Ng (1998) propose two generalizations of multivariate GARCH models in the General Dynamic Covariance (**GDC**) and Asymmetric Dynamic Covariance (**ADC**) models. They include as particular cases some representations previously described: VECH, BEKK, CCC and FARCH, as well as their asymmetric versions with the GJR approach. One advantage of this more general specification is that it allows the researcher to select the model that best fits the data by simply testing certain restrictions on the general model. They apply their models to the dynamic relations between large and small firm returns. The VECH, BEKK, CCC and FARCH models provide different estimations. Moreover, when drawing *news impact surfaces*, an extension of the *news impact curves* by Engle and Ng (1993), these also depend on the selected model. Therefore, the adequate election of the best specification for the data is very important, so they also provide several specification tests based on the tests provided by Engle and Ng (1993) and the regression-based misspecification diagnostics suggested by Wooldridge (1990, 1991). ADC models have been used, among others, by Ng (2000), Martens and Poon (2001) and Meneu and Torró (2003). In all studies, specific models contained in the ADC model are rejected in favor of the most general one.

Recently, Engle (2002) proposes the Dynamic Conditional Correlation (**DCC**) model, a new multivariate GARCH model that is particularly interesting for large systems. He also proposes its extension to the asymmetric case, the ASY-DCC model. Both models are estimated in two stages and their application to the volatility transmission and contagion analysis is still to be explored (see Suleimann (2003)). More recent works are extending the DCC model to allow for more flexible dynamic dependencies in the correlations, asymmetries and even regime switches (see Billio *et al*. (2003), Cappiello *et al*. (2006), Billio and Caporin (2005) and Pelletier (2006), among others).

All the models discussed until now assume that the error term and its conditional variance are stationary processes. However, Engle and Bollerslev (1986) introduce the terminology **IGARCH**, for those cases when the conditional variance behaves as a unit root process and shocks to h_t do not decay with time. This phenomenon known as "volatility persistence" has also been studied using Long Memory formulations. Bollerslev and Engle (1993) extend the IGARCH concept to the multivariate case. They apply it to the bivariate analysis of exchange rates and conclude that two individually IGARCH series can be combined in such a way that volatility persistence disappears. Thus, from a multivariate IGARCH model, we can obtain a univariate GARCH model with the sum of the coefficients in the variance equation being less than one. Kearney and Patton (2000) and Ewing *et al*. (2002) propose IGARCH specification tests both in the univariate and multivariate case. Similarly, Baille *et al*. (1996) and Bollerslev and Mikkelsen (1996) introduce, respectively, the fractionally integrated GARCH (FIGARCH) model and the fractionally integrated EGARCH (FIEGARCH) model. The first one has been applied, among others, by Brunetti and Gilbert (2000) to analyze volatility on the NYMEX and IPE crude oil futures markets. However, estimation and properties of IGARCH models still need further investigation and, therefore, empirical applications are still scarce in this area. Additionally, Susmel (2000) suggests that a near integrated behavior in volatility might be due to the presence of structural changes.

Another model to be taken into account is the one used by Fratzscher (2002) to analyze the integration process of European financial markets. Concretely, he uses a trivariate GARCH model with size and asymmetry effects in shocks and with time varying coefficients. It concludes that coefficients have changed with time. Three factors explain these changes in the integration process: exchange rates, currency policy convergence and real convergence, being the first factor the most relevant one. Finally, another new approach for modeling the conditional dependence in volatilities is the copula-GARCH model (Jondeau and Rockinger (2006)). They use their methodology to investigate the dependency structure between daily stock-market returns. Patton (2006a, 2006b) also gives important contributions in the study of time-varying copulas. He introduces the concept of conditional copula, proposes estimation models and applies them to the study of asymmetries in the dependence structure of a set of exchange rates. Similarly, Arakelian and Dellaportas (2003) derive a contagion test via copula threshold models and use it in a bivariate analysis of stock-market returns. However, empirical applications of these models in volatility transmission analysis are still a subject for further research.

In multivariate GARCH, the Maximum Likelihood (ML) estimation procedure has been widely used, due to its relative simplicity and the good properties its estimators have under ideal conditions. Thus, when the conditional normality hypothesis is correct, it is obvious that ML estimators are the most appropriate ones because, under certain regularity conditions, they are asymptotically efficient. However, as suggested by Engle and González-Rivera (1991) and Bollerslev and Wooldridge (1992), the conditional normality assumption may be too restrictive, especially in financial time series. Therefore, Bollerslev and Wooldridge (1992) propose Quasi-Maximum Likelihood (QML) estimation and conclude that these estimators applied to GARCH models are consistent even when the real distribution function is not Normal. Other estimation methods for GARCH models have been suggested in the literature: semiparametric methods (see Tapia and Thompson (1978), Engle and González-Rivera (1991) or Drost and Klaassen (1997)), Hansen (1982)'s Generalized Method of Moments (GMM) or non parametrics methods such as Kernel and Fourier. However, these methods have not been as popular in the empirical literature on volatility transmission as ML and QML.

It should not be forgotten that these multivariate models estimations are joint estimations. According to Ewing *et al*. (2002), in order to avoid the *generated regressor problem*, it is better to estimate jointly the mean and variance equations in a bivariate GARCH model than in two stages. However, most of the studies that propose to model the mean equation as a Vector Error Correction (VEC) model, first estimate the mean equation by OLS and, after that, they estimate the variance equation by ML or QML. This two stages procedure is, according to Tse (1999), asymptotically equivalent to a joint estimation of the VEC and GARCH models. This is so because the OLS estimator used in the VEC model is unbiased and consistent even in the presence of heteroskedasticity.

Regarding model selection between the numerous possibilities which have been analyzed, several useful tools for checking model adequacy have been provided. According to Tse (2002), diagnostics for conditional heteroskedasticity models applied in the literature can be divided into three categories: portmanteau tests of the Box-Pierce-Ljung portmanteau type, Lagrange multiplier (LM) tests and residual-based diagnostics. In particular, Tse (2002) provides the asymptotic distributions of the residual-based diagnostics for both univariate and multivariate GARCH models. Bauwens *et al*. (2005) also provide useful suggestions on diagnostic checking in multivariate GARCH models.

Once the existence of volatility spillovers has been analyzed, Bollerslev *et al*. (1994) propose to measure shock duration and persistence through the *half-life* analysis. It measures how many days pass until half of the initial shock is absorbed by the variance. Several studies such as Booth *et al*. (1997), Scheicher (2001) or Ewing *et al*. (2002) apply this analysis.

Similarly, Lin (1997) proposes the Volatility Impulse Response Function (VIRF), which is a useful methodology to analyze second moments' interrelations between different markets.

As a conclusion, research will now probably focus on new and simpler GARCH models, easier to estimate and, therefore, more useful in practice. For example, Alexander (2001) proposes the O-GARCH model. Similarly, Van der Weide (2002) suggests the orthogonal GO-GARCH, a simple model contained in the BEKK representation, and proposes an estimation method that avoids typical convergence problems in the estimation of multivariate GARCH models.

1.2.2 Regime Switching

Diebold (1986), Lamoureux and Lastrapes (1990), Hamilton and Susmel (1994) and more recent studies such as Diebold and Inoue (2001) or Edwards and Susmel (2003) suggest that an almost integrated behavior of volatility could be due to the existence of structural changes. Following this idea, Hamilton and Susmel (*op.cit.*) introduced ARCH models with changes in regime. In these models, ARCH parameters change according to a state or regime matrix of the variable in the previous period. Thus, a non-linear regime switching model allows the behavior of the series being modeled to depend on the state of the system. In related independent work, Cai (1994) proposed another parameterization of the regime switching ARCH model. Similarly, Gray (1996), Dueker (1997) and Haas *et al*. (2004), among others, introduce new versions of univariate regime switching GARCH models (see Marcucci (2005) for a review and comparison of a group of univariate Markov Regime-Switching GARCH (MRS-GARCH) models with a set of different standard GARCH models). However, all these models can be difficult to estimate, and that is the reason why there are not many empirical studies in the volatility transmission field.

Two general methodologies dealing with changes in regime can be differentiated in the literature that analyzes shock transmission. On one hand, studies such as those of Lamoureux and Lastrapes (1990), Aggarwal *et al*. (1999), Batra (2004) and Ewing and Malik (2005), previously commented, use simple GARCH models where changes in regime are introduced using dummies. Studies differ in the method chosen to detect regime changes. Most of them use the algorithm proposed by Inclan and Tiao (1994), but other studies such as Sansó *et al*. (2004) propose new tests for the detection of changes in the unconditional variance.

On the other hand, there is an important amount of empirical literature using the Switching ARCH or SWARCH proposed by Hamilton and Susmel (1994), where transition probabilities from one state to another are determined by a Markov chain. First of all, univariate GARCH processes are considered. If high persistence in volatility is observed, there exist the possibility of modeling the series with a univariate SWARCH(K,q):

$$\begin{aligned} y_t &= a_0 + a_1 y_{t-1} + \varepsilon_t, \qquad \varepsilon_t / I_{t-1} \approx N(0, h_t) \\ h_t / \gamma_s &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(\varepsilon_{t-i}^2 / \gamma_{s_{t-i}} \right) \end{aligned} \tag{11}$$

where K is the number of states and, for example, if $K=3$, then $s_t=1,2,3$ refers to the present volatility state (low, medium or high).

One of the γ_s values must be standardized to 1. Moreover, if $\gamma_s=1$, the rest of values for γ_s measure the conditional variance ratio for state s relative to state 1. If the probability of changing from the high volatility state is also high, then that high volatility is not lasting.

The probability law making the economy switch from one regime to another is generally represented by a Markov chain with K states and constant transition probabilities. The joint estimation of the three equations (mean, variance and probability of regime change) is done by ML.

Finally, models using SWARCH methodology normally start with an estimation of univariate models for each one of the series being analyzed and, then, use a bivariate version of the SWARCH model.

Ramchand and Susmel (1998), among other univariate studies, observe how correlations among markets increase when the dominant market is in the high volatility state. Therefore, bivariate analysis makes correlations to depend on the volatility state. Ramchand and Susmel (*op.cit.*) find common volatility states in certain countries but not in others. Moreover, they suggest that, once regime changes are taken into account, a Student's t distribution does not help explaining fat tails in the conditional errors distribution. However, in their case, better predictions are obtained from a GARCH-t model rather than a SWARCH. Similarly to them, Li (2004) adopts a Markov-Switching technique to identify the high/low volatility states of both individual and world markets to create four possible market state combinations.

Susmel (2000) introduces the E-SWARCH(K,q) and its multivariate version, both indicated for asymmetries modeling. As suggested in its conclusions, GARCH and asymmetric effects are reduced when regime changes are introduced.

Edwards and Susmel (2001) also apply a bivariate SWARCH model and conclude that high volatility states tend to be related to international crises. Their results find evidence of interdependency rather than contagion. It should not be forgotten that Longin and Solnik (2001) disagree with the previous studies and suggest that correlation is not linked to volatility *per se*, but with market trend.

Edwards and Susmel (2003) use a regime switching model to analyze interest rates' volatility in emerging markets. They suggest that standard GARCH models are not appropriate for emerging countries due to the existence of big shocks. Although a GARCH model estimated using a Student's t distribution could cope with thick tails, those models predict too much persistence in volatility. Thus, the summation of the GARCH model coefficients is near the unity. As an alternative, a model with three states is considered: low, medium and high volatility. If the probability of changing from the high volatility state is also high, then that high volatility does not have to be extremely persistent. The SWARCH model allows researchers to locate and date periods of high volatility and it is found that, in emerging markets, these tend to be the same even in geographically separated markets.

Billio and Pelizzon (2003) analyze volatility and shock spillovers before and after EMU in European stock markets. In order to do so, they use a multivariate Switching Regime Beta Model (SRBM) (see Billio and Pelizzon (2000)). They find that volatility spillovers from both the world index and the German market have increased after EMU for most European stock markets.

The first paper that considers switching copulas to study contagion is the paper by Rodriguez (2007). He explores whether financial crises can be described as periods of change in the dependence structure between markets. He models this dependence structure as a mixture of copulas, with parameters changing over time according to a Markov switching model.

Baele (2005) proposes four different bivariate models to explain stock market returns in Europe and US and concludes that the model that best describes data is a bivariate Normal model with regime changes. In this model, returns come from a mixture of two bivariate Normal distributions. The distribution to be used depends on the regime and coefficients in the Markov chain are constant. This methodology allows to decompose unexpected domestic returns in local, regional and global shocks, being the last ones the most important ones. In the univariate analysis it proposes a model with regime changes in the volatility transmission parameters, depending on innovations in the regional and global markets. Furthermore, it proposes a three stages estimation. In the first stage, four bivariate specifications are estimated for Europe and US and the best one is chosen. In the second stage, the model is estimated excluding each time from the European index the market being analyzed. Finally, innovations in European and US returns are orthogonalized and these returns are introduced in the estimation of univariate models. Baele (*op.cit.*) finds evidence in favor of contagion from the US market into European local markets, but not from the European aggregated index.

Lee and Yoder (2007) extended Gray (1996)'s univariate Generalized Regime Switching (GRS) model to the bivariate case. This model solves the problem of path dependence and they used it to estimate time-varying minimum variance hedge ratios for corn and nickel spot and futures prices.

In regime switching models, the general modeling strategy should follow some steps. First, analyze series in order to detect or not changes in regime. Second, try to model series with linear processes and obtain good residuals. Third, use one of the tests designed to detect non linearity. Fourth, if non linearity is found, decide the best way to model it. Finally, estimate the model and check that coefficients are significant and that it fits better than the linear model.

Taking into account the results obtained in the different empirical studies analyzed, variances, covariances and correlations seem to change with time and state. Furthermore, most of the studies suggest that high volatility states have a short length.

Finally, as there is already much literature analyzing unit roots and cointegration in the presence of non linearity, further investigation should focus on multivariate SWARCH models estimation.

We should not forget the relevant financial implications of modeling regime switches. It is well documented that volatility persistence and asymmetric effects are reduced when regime changes are introduced. Ewing and Malik (2005) suggest that accounting for volatility shifts considerably reduces the transmission in volatility and, in their case, it even removes the spillover effects. These results have important implications for building accurate asset pricing models, improving volatility forecasts of stock returns (see, for instance, Hamilton and Susmel (1994)) and improving risk management.

1.2.3 Stochastic Volatility

Stochastic Volatility (SV) models are another alternative to analyze volatility transmission between financial markets. These models, however, have not been as popular as the GARCH models, as it is suggested by the few existing empirical literature.

The most basic SV models introduced by Taylor (1982) consider volatility as an unobservable variable and model the logarithm of volatility as a stochastic linear model, normally an autoregressive process. They can be seen as discrete time approximations to the continuous time models frequently used in the literature (see Taylor (1994) for a detailed revision on SV models).

The main advantages of these models in contrast with GARCH models are: i) generalization to the multivariate case is much easier (see Harvey *et al*. (1994)) and ii) properties of the series being analyzed can be easily obtained. Detailed comparisons between ARCH models and SV models can be found in Shephard (1996) and Kim *et al*. (1998), among others. Franses *et al*. (2005) develop a simple test for GARCH against a Stochastic Volatility model.

In the univariate case, the simpler stochastic volatility model would be as follows:

$$\begin{aligned} y_t &= \sigma_t \varepsilon_t \\ \log \sigma_t &= h_t = \alpha + \beta h_{t-1} + \eta_t \end{aligned} \tag{12}$$

where $\varepsilon_t \sim IID(0,1)$, $\eta_t \sim NID(0,\sigma_\eta^2)$ and both errors are mutually independent. The necessary and sufficient condition to assure stationarity in y_t is that $|\beta|<1$. As it can be seen, one of the advantages of SV models in contrast with GARCH models is that they explicitly differentiate error in level, ε_t, and error in variance, η_t.

The main disadvantage of SV models is that, even assuming that ε_t is a Gaussian process, y_t is not conditionally Normal, and therefore estimation is not as easy as in the case of GARCH models. Estimation had usually been made with the Generalized Method of Moments (GMM). Nevertheless, Nelson (1988) and Harvey *et al*. (1994) independently proposed a Quasi Maximum Likelihood (QML) method, whose properties have been analyzed by Ruiz (1994a), concluding that this method is more efficient than the GMM. However, Andersen and Sorensen (1997) suggest that the QML procedure is not efficient if volatility proxies are not Gaussian. In fact, other methods such as Gibbs sampling (Mahieu and Schotman (1998)), Bayesian Markov Chain Monte Carlo (MCMC) (Jacquier *et al*. (1994)), Simulated Maximum Likelihood

(Danielsson (1994)) or Maximum Likelihood in closed form (Aït-Sahalia and Kimmel (2007)) have been proposed in the literature. Broto and Ruiz (2004) provide a survey regarding estimation techniques for SV models.

Apart from the conventional SV model from Taylor (1982), there exist several extensions. This model can be generalized so that h_t follows any kind of process (see Ruiz (1994b), Harvey *et al*. (1994), Billio and Sartore (2003) and Asai *et al*. (2006) for theoretical specifications and extensions of SV models). Within these extensions, we could highlight the multivariate extension of Harvey *et al*. (1994), the asymmetric SV models of Harvey and Shephard (1996), Danielsson (1994, 1998), So *et al*. (2002) and Jacquier *et al*. (2004) or the long memory SV model (see Comte and Renault (1998) and Breidt *et al*. (1998)). Similarly, Diebold and Nerlove's (1989) latent factor model can be regarded as a stochastic volatility model. Sentana (1998) discusses the relationship between Engle's factor GARCH model and a general class of conditionally heteroskedastic factor models, which includes the latent factor model as a special case. The factor multivariate SV model was first introduced by Harvey *et al*. (1994) and extended by Shephard (1996), Pitt and Shephard (1999), Aguilar and West (2000) and Chib *et al*. (2006), among others. Thus, multivariate SV models can also incorporate common factors. Wongswan (2006) and Lopes and Migon (2003) use SV models with factors and apply them to the analysis of shock transmission between markets. Moreover, Kalimipalli and Susmel (2004) introduce regime switching in a two-factor stochastic volatility (SV) model to explain the behavior of short-term interest rates. Similarly, Markov Switching Stochastic Volatility models can be found in So *et al*. (1998) and Casarin (2004), among others.

As it happens with GARCH models, SV models can also be estimated assuming that ε_t follows a Student's t or Generalized Error Distribution (GED).

Relative to the extensive theoretical and empirical literature on GARCH models, the SV literature is still in its infancy. Therefore, the majority of existing research in the SV literature deals with specifications or estimation techniques. So, there are still few empirical studies applying SV models to the analysis of shock transmission between financial markets. Among them, So *et al*. (1997) study stock market volatility in seven Asian countries. They decompose volatility into two components: basic and residual volatility, which enables them to calculate volatility of volatility. In SV models, *half-life* or volatility shock duration can also be analyzed. In this case, they estimate the model in two stages, as proposed by Harvey *et al*. (1994). In order to analyze volatility transmission between markets, univariate models are estimated and correlations between standardized residuals are calculated. This study provides evidence in favor of volatility transmission between the Asian financial markets analyzed. An alternative would be to use multivariate models.

Wongswan (2006) applies SV models to high frequency data, in particular, to stock market returns in 15 minutes intervals for the US, Japan, Korea and Thailand markets. In particular, he studies the effect of macroeconomic announcements in US and Japan on volatility and trading volume in Korea and Thailand. In this study, a SV model with two factors is estimated following the two stages procedure proposed in Andersen and Bollerslev (1998). In particular, it uses (1) a short term or mean reversion factor and (2) a long term or persistency factor. The first factor varies with information, measured as: i) a dummy for each macroeconomic announcement, ii) the size of announcement surprises and iii) the dispersion of announcement expectations.

Also, Lopes and Migon (2003) combine factor models with SV models. In this case, they analyze dependency among Latin American and US stock market indexes, modeling the factor's variance with a multivariate SV structure.

It seems that these multivariate factor SV models can be the solution to dimensionality and computational problems. Therefore, more empirical and theoretical effort should be placed in this kind of models.

1.3 Applications

In this section we specifically focus on certain aspects related to the empirical application of the methodologies analyzed before. In particular, we will analyze the different *financial markets* where these methodologies have been applied. Moreover, the *overlapping problem* coming from different markets' trading hours will be commented. Another aspect also related to the empirical application of these methodologies is the relation between *efficiency* and information transmission between markets. Finally, special attention is paid to *asymmetries* modeling.

1.3.1 Financial markets

The empirical literature has mainly focused on international shock transmission between stock market indices. However, the methodologies proposed can also be applied to analyze shock transmission between: i) cross-listed stocks, ii) stocks, indices or portfolios of large and small firms, iii) exchange rates, iv) interest rates and v) spot and futures markets, among others. Table 2 contains several examples of studies applied to each one of these markets.

Earlier studies analyzing interrelations between **stock market indices** mainly focused on developed markets, where data was reliable and easy to obtain. After the 1987 crisis, studies analyzing volatility transmission from developed to emerging markets started to appear. Differences between developed and emerging markets have been pointed out in several studies and must be taken into account when choosing between alternative methodologies. Bekaert and Harvey (1997) highlight four common features of stock returns in emerging markets: high average returns, high volatility, more predictable returns and low correlation with developed markets. Scheicher (2001) also finds no correlation between US and several emerging markets and suggests that, in contrast with developed markets, international spillovers tend to be in returns and not in volatilities. Besides, Aggarwal *et al*. (1999) point out that some emerging markets have returns with positive asymmetry, in contrast with developed markets. Thus, as there are several studies suggesting no normality in emerging stock markets returns, specifications with Student's t distributions could be more appropriate for this kind of countries.

In studies analyzing volatility transmission between different stock market indices, prices are denominated in local currencies or they are all converted into the same currency. Generally, the results obtained are the same in both specifications (see Hamao *et al*. (1990), Aggarwal *et al*. (1999) or Lee *et al*. (2004), among others). Finally, a recent study by Cifarelli and Paladino (2005) suggests that volatility modeling with exuberance indexes (excess stock market return over expected long-term bond return) is more accurate than modeling with stock returns.

In the case of empirical applications to **cross-listed stocks**, the empirical literature is not that extensive, probably due to its higher complexity. As suggested by Xu and Fung (2002), there are many factors that must be taken into account when analyzing information transmission in one single stock traded in different markets. Although they find that trade volume does not influence this relation, other factors such as the firm's degree of internationalization, different trading hours and microstructure aspects can play an important role.

The empirical literature on volatility transmission between **small and large firms** reaches different conclusions, the most accepted one being that large firms' returns can affect small firms' volatility, but small firms' returns do not affect large firms' volatility (see Conrad *et al*. (1991) and Kroner and Ng (1998)). Moreover, the existence of asymmetric effects is generally accepted (see Pardo and Torró (2007), among others). However, Ewing and Malik (2005) indicate that accounting for volatility shifts considerably reduces the transmission in volatility and, in essence, removes the spillover effects.

Maybe one of the most interesting applications is that of volatility transmission between **spot and futures markets**. Chan *et al*. (1991), Cheung and Ng (1996), Aragó *et al*. (2000, 2003), Lafuente (2002) and Meneu and Torró (2003) find evidence of spillovers in both directions, whereas Koutmos and Tucker (1996), Tse (1999) and Fung *et al*. (2005) find more important volatility spillovers from future to spot markets.

There is also a considerable amount of literature dedicated to analyze volatility transmission between **exchange rates**. Most of these studies propose multivariate GARCH methodologies (see, Bollerslev (1990), Ito *et al*. (1992) or Kearney and Patton (2000), among others), although more recent studies, such as Chowdhury and Sarno (2004), also apply multivariate Stochastic Volatility models to analyze volatility spillovers across exchange rates. In contrast, there are no many empirical studies analyzing volatility transmission between different **interest rates**. Ayuso *et al*. (1997), Edwards and Susmel (2003), Abad and Novales (2004) and Alonso and Blanco (2005) are among those few existing studies.

Caporale *et al*. (2002) analyze relations between **stock markets and exchange rates**. If there exist, as they suggest, bidirectional volatility spillovers, regulatory authorities should take into account both effects when determining their intervention policies. Finally, there are also studies dealing with volatility transmission in electricity markets (see Worthington *et al*. (2005)) and in different commodity markets (see Ewing *et al*. (2002) for the oil and natural gas markets or Xu and Fung (2005) for precious metals markets, among others).

The introduction of dummies to model day of the week effects, both in the mean and variance equations, has also been popular in the empirical literature. Although evidence is contradictory and depends on the markets being analyzed, these variables are generally significant in the mean equation but not in the variance equation (see, among others, Peña (1992), Karolyi (1995) and Kim (2005)).

Regarding data frequency, most of the studies analyze daily or intradaily returns (open to close, close to open and close to close). These are mostly recent studies and they present modeling difficulties due to seasonality and microstructure features. There is not a clear relation between data frequency and methodology used, with the only exception of Regime Switching models, which are obviously mostly used in weekly or lower frequencies.

Some studies, such as Ghose and Kroner (1996) or Kearney and Patton (2000), which analyze different frequency data, suggest that in lower frequencies there is less volatility transmission. This can be interpreted as evidence in favor of markets transferring information when they are in active periods and not in calm periods. Moreover, short term spillovers may not be detected when working with low frequency data.

It is very important to decide how volatility is measured or introduced into the model in the different methodologies analyzed. Several studies use squared residuals as a proxy for the influential market volatility (see, for example, Hamao *et al*. (1990), Susmel and Engle (1994) or Lee *et al*. (2004)). Other studies introduce directly as a regressor the estimated conditional variance (see Hamao *et al*. (1990) or Kim (1994)). However, there are other possibilities such as using implied volatilities (Jimeno (1995)), Garman-Klass volatilities (Kim (*op.cit.*)) or any of the measures suggested by Engle and Gallo (2006), such as realized volatilities or high-low spreads. Although conclusions reached regarding volatility transmission using either one or another specification may be the same (see Hamao *et al*. (1990) or Kim and Rogers (1995)), the different interpretations must be taken into account.

The theoretical properties of realized volatility have been discussed from different perspectives in a number of recent studies including Andersen *et al*. (2000, 2001, 2003a,b, 2006) and Barndorff-Nielsen and Shephard (2001,2002a,b, 2004, 2005). The studies by Barndorff-Nielsen and Shephard also deal with the use of realized volatility in conjunction with Stochastic Volatility models. As an example of the use of this volatility measure in volatility transmission modeling itself, Melvin and Peiers (2003) examine volatility spillovers in exchange rates across regional markets using the realized volatility of high-frequency data.

Finally, it should be highlighted that some studies, applying different methodologies to the same markets, frequencies and sample, reach different conclusions regarding volatility transmission. For instance, Hamao *et al*. (1990) and Susmel and Engle (1994) offer contradictory conclusions regarding the relationship between the New York and London stock markets, probably due to differences in estimation methods and asymmetries modeling. Therefore, it is important to understand and test methodology's assumptions and choose the one that best fits the markets being analyzed.

Therefore, the main results extracted from this section are as follows. First, empirical applications of volatility transmission models have mainly focused on stock market indices of developed countries, though there are empirical studies on other financial markets. Second, there is not a clear relation between data frequency and methodology used. Third, in lower frequencies there is less volatility transmission. Fourth, volatility can be measured or introduced into the model in different ways. And, fifth, it is determinant to check and choose the specification that best fits the data.

1.3.2 Overlapping problem

When analyzing shock transmission between different financial markets, differences in trading hours and trading calendar must be taken into account. When analyzing future and spot markets or large and small firms, this problem does not normally appear because markets in the same country tend to overlap trading hours and calendar. However, when analyzing volatility transmission between international stock markets or between ADRs and their underlying assets, the overlapping problem must be considered.

Another technical problem also related with nonsynchronous trading, this time regarding stocks making up a particular index, is the so-called *stale quote problem*. This problem was analyzed, among others, by Stoll and Whaley (1990) and Lo and MacKinlay (1990). It appears because, when markets open, not all stocks marking up indices start being traded. This fact produces autocorrelation in return series and has been detected in most of the studies analyzing stock market indices, among them, Lin *et al*. (1994), Bae and Karolyi (1994) and Kim and Rogers (1995). To minimize this problem, the opening quote is chosen as a price index quoted 15 or 30 minutes after the stock market official opening time (see Hamao *et al*. (1990) or Lin *et al*. (1994)) or simply, as many studies do, a moving average MA term is included in the mean equation. As suggested by Lin *et al*. (*op.cit.*), not taking into account this effect could alter results as it could produce false relations or spurious lagged spillovers.

Nevertheless, in this section we will mainly focus on the nonsynchronous trading problem in international stock markets.

In general, three different situations may exist: a) total overlapping, b) no overlapping and c) partial overlapping. The two first cases are easier to handle, being the third one the most complicate one.

There is no clear relationship between overlapping circumstances and methodology applied. Only in the case of non overlapping markets there seems to exist a preference for GARCH models and a clear differentiation between intradaily open to close (O-C) and close to open (C-O) returns. The rest of cases mostly combine cross-correlation and cointegration analysis with GARCH methodologies.

The easiest case to interpret is **total overlapping markets** (see Karolyi (1995) for US-Canada or Booth *et al*. (1997) for European indices). In this case, conditional moments in the different markets refer to the same time period and the existence of lead-lag relations or the effect of a global shock are easier to analyze. Moreover, both close to close (C-C) and O-C returns can be used.

Regarding **non overlapping markets**, only O-C returns should be considered in the analysis. This is so because there could exist dependency relations not related to information transmission. Some examples of studies using O-C data in non overlapping markets are Hamao *et al*. (1990), Bae and Karolyi (1994) and Koutmos and Booth (1995). If C-C returns are used, returns of the first market to open will depend on lagged returns of the other market. However, using C-C returns does not avoid the spillover effect found in opening prices and predicted by ICAPM models.

In any case, working with returns calculated for periods that do overlap can introduce a bias in the relation between both markets because the contagion coefficient includes both causality and correlation coming from contemporarity. Therefore, using C-O and O-C returns could reduce this problem. Moreover, Hamao *et al*. (1990) do not find important differences in empirical results when using these returns or C-C returns.

In the case of **partially overlapping markets**, a jump in prices can be observed in the first market to open when the second one starts trading, reflecting information contained in the opening price. Therefore, this could make volatility increase in this first market. Moreover, as suggested by Hamao *et al*. (1990), a correlation analysis between partially overlapping markets using C-C returns could produce false spillovers, both in mean and volatility. This is so because it is difficult to separate effects coming from the foreign market from those coming from the own market while it remains closed.

There are several **solutions** in order to artificially synchronize international markets. In the case of US, information transmission with other markets can be analyzed through ADRs, which will share trading hours with the North American market. The problem is that there are no many ADRs, they are not actively traded and there are microstructure differences between the North American stock market and that from the original country (Wongswan (2006)). Other studies prefer to use weekly or two days returns (Forbes and Rigobon (2002)) in order to avoid the overlapping problem. Finally, Martens and Poon (2001) analyze different procedures proposed in Riskmetrics (1996) and Burns *et al*. (1998) to calculate artificially synchronized correlations from nonsynchronized returns. They compare both measures and prefer the second one, although they suggest more investigation should be made in this field.

Some studies analyzing several international markets (see Ito *et al*. (1992)) propose to divide one day *t* in separate non overlapping markets or regions, for instance: Pacific, Japan, Europe and US. Market *i* will have information from *t-1* but also information from *t* coming from those markets that were opened before. It is important to correctly specify temporal subindices in order to analyze the existence of *heat waves* or *meteor showers*. Similarly, Melvin and Peiers (2003) identify five sections: Asia, non overlapping period Asia/Europe, Europe, overlapping period Europe/America and America. These five non overlapping market segments are the basis for their volatility transmission models, which use daily measures of integrated or realized volatility for each region.

Studies such as King and Wadhwani (1990), Jimeno (1995) or Cotter (2004) propose to differentiate those cases where: i) both markets are open, ii) both are closed and iii) one is opened and the other closed, and analyze them separately, with the same model adapted to each circumstance. Depending on the case, the other market's influence will be contemporaneous, lagged or even inexistent. King and Wadhwani (*op.cit.*), use in their contagion model the so-called *shadow index*, relative to the period when the market is closed. Moreover, they extend their analysis to several markets, proposing a model with exogenous regime switches depending on the overlapping circumstance.

Some studies directly choose to analyze non overlapping markets, due to its simplicity. Even in some cases, when there is overlapping they consciously ignore it or eliminate it from the sample (see Susmel and Engle (1994)). Some other studies do not take the overlapping problem into account in their models and simply suggest that it may hamper the correct interpretation of results. From our point of view, the overlapping problem should be considered and the methodology used should be adapted to the kind of overlapping existing between the markets analyzed.

1.3.3 Efficiency

The concept of efficiency has been frequently linked to financial markets' interrelations. In particular, traditionally, it has been related to mean relations between the different markets analyzed. Granger (1986) argues that two series of prices from efficient markets cannot be cointegrated, otherwise one price could be used to predict the other. This would go against the efficient market hypothesis in its weak sense. According to it, asset prices incorporate all the available information. Similarly, if we take Fama (1970)'s definition of static efficiency, markets would not be efficient when cointegration relations exist. That definition describes a market as efficient when participants rationally exploit all the available information and the equilibrium expected returns are constant.

Sephton and Larsen (1991) called into question the direct relationship between the existence of cointegration relationships and the absence of efficiency. They showed that the statement is excessively ambitious as cointegration results can differ substantially depending on the period and the sample frequency, and the existence or not of structural changes. Even the method for estimating a cointegration relationship can be determinant.

Other studies link the concept of efficiency to the existence of arbitrage opportunities. Therefore, in this case, cointegration and efficiency would not be incompatible. Dwyer and Wallace (1992) and Engel (1996), among others, pointed out that although the existence of cointegration implies prediction, it does not necessarily imply that arbitrage opportunities exist. Transaction costs, for instance, could eliminate the differences revealed by the prediction. Similarly, Darrat and Zhong (2002) argue that predictability alone does not necessarily imply market inefficiency, unless the implied trading rule can also yield risk-adjusted excess returns.

But let us extend the debate to second moments and volatility transmission. Engle *et al*. (1990b) analyze exchange rates markets and find evidence in favor of *meteor shower* effects. As they suggest, this could go against efficiency in the strict sense. It should be noticed that although returns are not predictable, volatilities are.

As it also happens in the more theoretical literature, in the empirical literature there exist different definitions of efficient markets, although all of them seem to point in the same direction. Susmel and Engle (1994) describe a market as efficient when there are neither mean nor volatility spillovers from another market that closed some hours in advance. This is so because that *old* information is supposed to have been already incorporated into domestic returns. Therefore, they relate efficiency to rapidly incorporating information from external markets. Fratzscher (2002) also uses this definition in his analysis of European stock markets. A market is more efficient when relevant information is rapidly incorporated into asset prices. Assuming totally efficient markets, information in *t-1* should not affect returns in period *t*. Thus, he finds evidence of higher integration and efficiency in European markets following monetary union. Similarly, Kim and Rogers (1995) define as efficient market that which incorporates other markets' information into its opening price. In particular, they conclude that, following the Korean's market liberalization, volatility spillovers from international markets have increased.

As a conclusion, it seems that in the mean analysis of returns, efficiency should be related to the existence of arbitrage opportunities, whereas in the variance analysis, a market is efficient when spillovers are contemporaneous and have a short life.

1.3.4 Asymmetry

The importance of modeling this effect comes from the need of obtaining better model fits. As suggested by several authors, conclusions obtained from volatility transmission models could be erroneous when asymmetries are not modeled (Susmel and Engle (1994) and Bae and Karolyi (1994)).

Some studies use the *asymmetry* concept to refer to the differences found in the direction of spillovers or causality relations between markets. Thus, for example, Hamao *et al*. (1990) find asymmetries in the London-Tokyo relation, meaning that volatility spillovers are found in one direction but not in the other. This concept of asymmetry should not be confused with the one being analyzed, which is more related to shocks' sign and size.

Several explanations have been proposed in the literature for the asymmetry in the volatility of equity returns. One is the leverage hypothesis due to Black (1976). According to this explanation, a drop in the value of a stock increases financial leverage, which makes the stock riskier and increases its volatility. Although the concept of leverage effect has become almost synonymous to asymmetric volatility, some authors suggest other explanations, such as the volatility feedback effect (Pindyck (1984), French *et al*. (1987) and Campbell and Hentschel (1992)), which defines asymmetry as the result of misspecifying the volatility process or coming from the incompleteness of the information used to form conditional volatility.

Although the concept of asymmetry as the different impact of negative and positive shocks on volatility has its origin in Black (1976), French *et al*. (1987) and Schwert (1990), in this case we are interested in its application to volatility transmission between markets. This concept has been mostly used in GARCH methodologies. Several univariate models try to model this feature, being the most popular in the empirical literature those of Nelson (1991) (EGARCH) and Glosten, Jagannathan and Runkle (1993) (GJR-GARCH).

Nelson (1991)'s EGARCH model proposes the following specification for the conditional variance:

$$\ln(h_t) = \alpha_0 + \alpha_1\left(\varepsilon_{t-1} / h_{t-1}^{0.5}\right) + \gamma_1\left|\varepsilon_{t-1} / h_{t-1}^{0.5}\right| + \beta_1 \ln(h_{t-1}) \tag{13}$$

In the GJR-GARCH model by Glosten, Jagannathan and Runkle (1993), the original GARCH specification is modified including a dummy variable I_{t-1} that takes value 1 if $\varepsilon_{t-1} > 0$ and 0 otherwise:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 I_{t-1} + \beta_1 h_{t-1} \tag{14}$$

Although these specifications have been the most popular ones, there exist other specifications such as the PNP-GARCH model used in Bae and Karolyi (1994) or the T-GARCH model used in Hsin (2004). There exist other possibilities to models asymmetries such as the contemporaneous asymmetric GARCH model of El Babsiri and Zakoian (2001) or the quadratic ARCH model of Sentana (1995) although, as far as we know, they have not yet been used to analyze volatility transmission. The selection between several asymmetric specifications should be made in terms of conventional measures of goodness of fit and/or parameter significance tests. Alternatively, Ding *et al*. (1993) propose a general model, the APARCH, which includes several asymmetric specifications.

Without any doubt, Engle and Ng (1993) is an important reference for asymmetries modeling. In this study, the concept of *News Impact Curve* and its functional form for several GARCH specifications are introduced. This curve represents the functional relationship between conditional variance at time *t* and the shock term (error term) at time *t-1*, holding constant the information dated *t-2* and earlier. If there is asymmetry in the series, either the slopes in both sides of the curve are different or the curve's centre is in a point where $\varepsilon_{t-1} > 0$. Moreover, they introduce some very popular specification tests: the *Sign Bias Test* (SBT), *Negative Size Bias Test* (NSBT) and *Positive Size Bias Test* (PSBT). Once a GARCH model has been estimated, these tests analyze whether an asymmetry dummy variable is significant in the prediction of squared residuals. These tests can be used individually or jointly, the last option resulting in a more powerful test.

Engle and Ng (1993) analyze several asymmetric specifications and conclude that asymmetry does not only depend on sign, but also on innovation size. Moreover, they find evidence in favor of the GJR specification when compared to the EGARCH.

Bae and Karolyi (1994) apply these tests and also extend the graphical concept to the so-called *International News Impact Curve*.

Another study that had a lot of influence on the volatility transmission analysis was Kroner and Ng (1998). The authors propose two generalizations of multivariate GARCH models in the *General Dynamic Covariance* (GDC) and *Asymmetric Dynamic Covariance* (ADC) models. They include as particular cases some representations previously described: VECH, BEKK, CCC and FARCH, as well as their asymmetric versions with the GJR approach. They apply their models to analyze dynamic relations between large and small firm returns and use Maximum Likelihood techniques and a two stages procedure to estimate their models. Furthermore, they extend Engle and Ng (1993)'s *News Impact Curves* to the multivariate case in the so-called *News Impact Surfaces*. They also provide several specification tests because, as also suggested by Engle and Ng (*op.cit.*), the Ljung-Box test cannot detect misspecification due to asymmetries. Finally, Kroner and Ng (1998) extend asymmetries modeling to covariances. It should not be forgotten that, as stated in Martens and Poon (2001), there is evidence of asymmetry in variances, covariances and correlations.

Meneu and Torró (2003) use the ADC model and obtain the Volatility Impulse Response Function (VIRF) for asymmetric multivariate GARCH structures, extending Lin (1997) findings for symmetric GARCH models.

Longin and Solnik (2001) detect asymmetries in correlations. This means higher correlations in bear markets and lower correlations in bull markets. Based on them, Ang and Bekaert (2002) show that a regime-switching (RS) model reproduces these asymmetric exceedance correlations, whereas standard models, such as multivariate normal or asymmetric GARCH models, do not. Similarly, Martens and Poon (2001) find that correlations increase when there has been a large negative shock the previous day, but they are much less sensitive to large positive shocks and returns smaller than 2% in absolute value. Therefore, correlations respond to volatility only in the case of large negative returns.

Thus, it seems that there exists enough evidence of asymmetry in variances and covariances, and more effort should be made on the analysis of correlation asymmetries and in their causes, in any case. In this sense, Bae and Karolyi (1994) suggest that the lack of trade volume variables, microstructure variables or regime changes in the model could cause the existence of asymmetries.

Although GARCH specifications have been the most popular to model asymmetries, other methodologies also include asymmetric versions. For instance, there exist asymmetric extensions of Stochastic Volatility models (Harvey and Shephard (1996)). Similarly, Susmel (2000) proposes an asymmetric E-SWARCH model and suggests that modeling regime changes reduces GARCH and asymmetric effects.

Therefore, choosing the correct model specification becomes crucial, both *a priori* in the data analysis process and *a posteriori*, applying different specification and goodness of fit tests.

General specifications such as Kroner and Ng (1998), nesting other more restrictive specifications, enable researchers to select the final model (with or without asymmetry) using some restriction tests. This is an easy procedure and avoids *ad hoc* selection.

1.3.5 Extensions

Once the empirical and theoretical literature has been analyzed, it would be interesting to highlight emerging investigation topics and questions that remain still unanswered, which could open future investigations lines.

Here is a list of open issues/research topics:

1. Further developments on multivariate SV models (estimation methods, new models and empirical applications).
2. Providing realistic but parsimonious multivariate models for large dimensional systems.
3. Improving software for multivariate models estimation.
4. Further developments of multivariate diagnostic tests.
5. Analyzing volatility transmission between cross-listed stocks.
6. Analyzing volatility transmission through sectoral indices.

7. Effects of microstructure over volatility transmission mechanisms.
8. Analyzing volatility transmission through ultra high-frequency data.
9. Using realized volatility on volatility transmission models.
10. Causes and consequences of volatility transmission.

More details in these areas and further and more specific research topics can be found in Engle (2002), Asai *et al*. (2006) and Bauwens *et al*. (2006).

Regarding methodologies, GARCH models have been the most popular in both applied and theoretical literature. Thus, nowadays, empirical studies tend to focus on other methodologies such as Stochastic Volatility models and models with Regime Switching. In particular, multivariate factor SV models seem to have a promising future. The literature has recently focused on providing and comparing different estimation methods but, surely, further new models and empirical applications are warranted.

In GARCH methodology it would be necessary to get deeper in multivariate model estimation, in concrete, improving computational convergence possibilities. In this sense, more recent models such as Engle (2002)'s DCC or Van der Weide (2002)'s GO-GARCH, pursue this idea of estimation simplicity and speed. Similarly, further research should be devoted to improve software for estimation. Brooks *et al*. (2003) examine the relative small number of software packages that are currently available for estimating multivariate GARCH models, in spite of their widespread use. Finally, further research should be also devoted to develop multivariate diagnostic tests. Since estimating multivariate GARCH models is time-consuming, it is desirable to check both *ex ante* and *ex post* the adequacy of the GARCH specification.

Regarding financial markets, there are certain relations that have not been sufficiently analyzed. For instance, relations between individual stocks traded in different markets or relations between different sectoral indices. In the first case, cross-listed stocks, e.g. American Depository Receipts (ADRs), is an alternative and important way of achieving international diversification and, therefore, information flows between ADRs and their underlying assets must be further analyzed. In the second case, studies such as Roll (1992) or Arshanapalli *et al*. (1997) suggest that international movements should not be measured with general stock market indices because they have different industrial composition. Thus, these studies propose using indices from the same industry in different countries in order to analyze international interrelations. General indices do not differentiate country effect from volatility sources coming from the industry.

Without any doubt, another topic that is becoming increasingly important is market's microstructure. The real short term relationship between markets can be affected by microstructure differences such as institutional features or trade rules. These differences could make the correct interpretation of results difficult. Therefore, more investigation on the effects of microstructure over volatility transmission mechanisms would be welcomed.

The development of information treatment systems in the last decades has favored the appearance of high frequency databases, which have been a great impulse for empirical studies. Many financial markets offer detailed information on transactions and quotes, which allows the creation of time series of prices, volume, demand and so on, with almost continuous frequency. However, this information wealth introduces new modeling difficulties, such as regular components or seasonality (see Andersen and Bollerslev (1997)). In this sense, some studies such as Werner and Kleidon (1996), Chan *et al*. (1996) or Kofman and Martens (1997), analyze relations between different markets in the very short term (intraday) controlling for seasonality in volatility. Similarly, continuous time Stochastic Volatility models will be, without any doubt, useful in the development of future volatility transmission models with high-frequency data. This is relevant because continuous time models are everywhere in financial theory and derivative pricing. Finally, as suggested by Engle (2002), it will be desirable to find models based on irregularly spaced data.

Probably due to the lack of high precision databases, researchers have mainly used closing prices data, when volatility transmission could also be analyzed using other variables such as bid-ask quotes or trade volume. Also in this sense, realized volatilities will surely be present in future research. According to Andersen *et al*. (2003a), two directions for future research are apparent: (1) continued development of methods for exploiting the volatility information in high-frequency data, and (2) volatility modeling and forecasting in the high-dimensional multivariate environments. The realized volatility concept readily tackles both, even better when combined with Stochastic Volatility models.

Finally, literature also seems to be aware that understanding how shocks are transmitted between markets is not enough, and causes and consequences of these transmissions must be further analyzed.

1.4 Conclusion

After several years of research on information transmission between financial markets, many questions remain still unanswered. The literature has mainly focused on the empirical analysis, requiring the theoretical part further investigation. Increasing availability of more complete databases, technological development, globalization and increasing financial market integration, among other reasons, raise even more the interest in this field.

This study reviews the most relevant methodologies applied to the analysis of volatility transmission between financial markets: GARCH models, Regime Switching models and Stochastic Volatility models. In addition, it covers several concrete aspects such as their scope of application, the overlapping problem, the concept of efficiency and asymmetry modeling. It seems quite clear that the best methodology to be used will depend on the hypothesis to be contrasted, serving in many cases some methodologies as complementary to the others. In fact, most of the studies use correlation and cointegration analysis as a complement to the short term analysis. Finally, emerging topics and unanswered questions are identified, serving as an agenda for future research.

We hope this survey, although necessarily brief and selective, has given the reader an idea of the methodological richness and the variety of conclusions in which it derives. Despite the discrepancies found in the empirical literature, some ideas seem to be shared by most of the studies. Correlation coefficients between different financial markets' returns tend to be small, positive and changing in time. It is not clear whether there is or there is not a direct or indirect relation between volatility and correlation. Furthermore, it is not clear whether this relation exists with volatility or market trend.

From our point of view, markets tend to increase or reduce their common movements in periods of high volatility depending on the factors or common shocks producing them. What it seems quite clear is that variances, covariances and correlations contain asymmetries and are changing in time. Finally, classical correlation measures, cointegration and unit root tests can be affected by the existence of conditional heteroskedasticity.

Furthermore, if, as some studies suggest, the relation between contagion and volatility was always positive, portfolio diversification would not be an adequate strategy. However, if this relation depended on the existence of common factors, the existing causality should be determined and international or intersectoral diversification would then be justified. Anyway, those factors could be observable, unobservable, local, regional or global. Evidence in this ground is diverse and it will surely depend on the markets being analyzed. Finally, although it seems quite clear that volatility is predictable, this will not affect financial markets' efficiency.

Some guidelines for further research in volatility transmission models have been given in the survey. With the increased availability of new and more complete high frequency databases, further theoretical and empirical studies will surely emerge. Multivariate SV models are particularly suited for that kind of data. However, as we mentioned, relative to the extensive theoretical and empirical literature on GARCH models, the SV literature is still in its infancy. Therefore, further developments on multivariate SV models will be surely welcomed. Moreover, both in GARCH and SV, additional effort should be devoted to provide realistic but parsimonious models for large dimensional systems.

Understanding the information transmission process between markets is crucial for asset valuation, risk management and economic policy. As suggested by Karolyi (1995), an incorrect understanding of market interrelations could result in inadequate or even counterproductive regulatory policies. Therefore, the different methodologies proposed should be used by researchers and analysts to determine where shocks come from, how and where they are transmitted and, if it is the case, how to control them.

As a conclusion, as it seems evident that there is no general methodology that could embrace every existing relation, market and hypothesis, we hope to have motivated the development of further research in the field.

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Table 1: Studies reviewed and GARCH methodology

AUTHOR/S	N	MEAN EQUATION	VARIANCE EQUATION	ESTIMATION
Bollerslev (1990)	5	Intercept	CCC(1,1)	ML-BHHH
Engle, Ito and Lin (1990)	n	-	GARCH	ML-BHHH
Engle, Ng and Rothschild (1990)	-	-	FARCH	ML-BHHH
Hamao, Masulis and Ng (1990)	1	MA(1) + 1 dummy + external shocks	GARCH(1,1)-M + 1 dummy + volatility external shocks	2 stages (ML-BHHH)
Chan, Chin and Karolyi (1991)	2	AR(1) + 2 dummies	GARCH(1,3)	ML-BHHH
Conrad, Gultekin and Kaul (1991)	1,3	ARMA(1,1)	GARCH(1,1)-M + res2(other market) / GARCH(1,1)-M	ML-BHHH
Ito, Engle and Lin (1992)	n	-	GARCH	QML
Peña (1992)	1	MA(q) + other regressors	GARCH(1,1) + other regressors	ML-BHHH
Bollerslev and Engle (1993)	2	-	IGARCH(1,1)	QML
Engle and Susmel (1993)	-	-	FARCH	-
Bae and Karolyi (1994)	1	MA(2) + dummies	GARCH(1,2) + res2(US) + res2(J) + asymmetry (GJR and PNP) + dummies	2 stages (QML-BHHH)
King, Sentana and Wadhwani (1994)	-	-	FARCH	ML-BHHH
Lin, Engle and Ito (1994)	1	Linear regression with external shocks	GARCH(1,1)-M, AS, SE	2 stages (ML, QML)
Susmel and Engle (1994)	1	MA(1) + information other market	GARCH(1,1)-M-t + information other market + asymmetry	ML-BHHH, QML-BHHH
Karolyi (1995)	2	VAR(5) + 2 dummies	BEKK(1,1,1) / CCC(1,3) / univariate GARCH(1,3) / + 2 dummies	ML-BHHH
Kim and Rogers (1995)	1	MA(1) + 4 variables (volatility)	GARCH(1,1)-M-t + 4 variables (volatility)	ML-BHHH
Koutmos and Booth (1995)	3	VMA(3)	EGARCH(1,1) with CCC	ML
Longin and Solnik (1995)	2	Linear regression	CCC(1,1) + 2 variables	QML
Pérez and Torra (1995)	2	VAR(1)	BEKK(1,1,1)	ML
Cheung and Ng (1996)	1	MA(1)	GARCH(1,1)	2 stages (ML, CORR)
Karolyi and Stulz (1996)	2	Linear regression	CCC(1,1) + regressors	QML-BHHH
Koutmos and Tucker (1996)	2	VEC(1)	EGARCH(1,1) with and without CCC	ML-BHHH
Ayuso, Haldane and Restoy (1997)	1	VEC(1)	EGARCH(1,1) + exogenous variables	ML
Booth, Martikainen and Tse (1997)	4	VAR(1)	EGARCH-t with CCC	ML-BHHH
Darbar and Deb (1997)	2, 4	AR(1)	BEKK(1,1,1)-t	ML
De Santis and Gerard (1997)	n	Conditional CAPM	Diagonal GARCH(1,1)	QML-BHHH
Kroner and Ng (1998)	2	VAR(10) + asymmetry dummy	GDC, ADC	2 stages (OLS, ML)
Ramchand and Susmel (1998)	1, 2	AR(1)	SWARCH(2,1,2) with CCC between states	ML
Aggarwal, Inclan and Leal (1999)	1	Intercept / AR(1)	GARCH(1,1) + regime switching dummy	QML-BFGS
Niarchos, Tse and Young (1999)	2	VMA(1)	EGARCH(1,1)-t with CCC	ML
Tse (1999)	2	VEC(1)	EGARCH(1,1)-t with CCC + dummies	2 stages (OLS, ML)

Table 1: (Continued)

AUTHOR/S	N	MEAN EQUATION	VARIANCE EQUATION	ESTIMATION
Aragó, Blasco and Corredor (2000)	2	VEC(1)	CCC(1,1) / CCC(1,1) + asymmetry	ML
Brooks and Henry (2000)	3	VARMA(1,1) + 1 dummy	BEKK(1,1,1)-GJR	QML
Fong and Chng (2000)	2	ARMA(1,1) + 5 dummies	CCC(1,1)	QML
Kearney and Patton (2000)	3-5	Intercept	BEKK(1,1,1)	ML-BHHH
Ng (2000)	1, 2	VAR(1)	GARCH(1,1)-ADC / GARCH(1,1)-BEKK with and without asymmetry	ML-BFGS
Pyun, Lee and Nam (2000)	1	Linear regression	GARCH(1,1) + trade volume+ squared residuals other market (res2)	2 stages (ML)
Susmel (2000)	1, 2	AR(1)	E-SWARCH	ML
Assoé (2001)	3	VAR(3)	E-GARCH(1,1) with CCC	QML-BFGS
Edwards and Susmel (2001)	2	VAR(1)	SWARCH(2,1)	ML
Isakov and Pérignon (2001)	2	VAR(1)	BEKK-GJR	ML-BHHH
Martens and Poon (2001)	2	Intercept	ADC	ML
Scheicher (2001)	4	VAR(1)	CCC(1,1)	ML-BHHH
Alaganar and Bhar (2002)	2	VAR(1)	GARCH with correlation affected by external shocks	ML-BHHH
Bera and Kim (2002)	2	Linear regression	CCC(1,1)	ML-BHHH
Caporale, Pittis and Spagnolo (2002)	2	AR(1)	BEKK(1,1,1)	QML
Ewing, Malik and Ozfidan (2002)	2	Intercept	BEKK(1,1,1)	ML-BHHH
Fratzscher (2002)	3	Linear regression with instrumental variables	GARCH with time variable coefficients	ML-BHHH
Illueca and Lafuente (2002)	1	AR(k)	GJR-GARCH(1,1)	ML-BHHH
Lafuente (2002)	2	VEC(1)	GARCH with no CCC and a U-shaped intraday pattern for volatility	ML-BFGS
Wang, Rui and Firth (2002)	1	Linear regression with dummies	GJR-GARCH(1,1)	2 stages (QML)
Xu and Fung (2002)	2	ARMA	Asymmetric GARCH	ML-BHHH
Aragó, Corredor and Santamaría (2003)	2	VEC(1)	GJR-GARCH(1,1) with CCC affected by structural changes + dummies	ML-BHHH
Edwards and Susmel (2003)	1, 2	AR(1)	SWARCH(3,1) / SWARCH(2,1)	ML
Meneu and Torró (2003)	2	VEC(10) + threshold term	ADC	QML
Miyakoshi (2003)	2	VAR(1) + US returns as exogenous variable	EGARCH(1,1) + US volatility as exogenous variable	ML
Tse, Wu and ANDoung (2003)	2	VMA(1)	EGARCH(1,1)-t with CCC	QML
Abad and Novales (2004)	1	Intercept + day dummies	GARCH(1,1)-M-GJR + day dummies + standard deviation 1-month rate	QML
Batra (2004)	1	Intercept	EGARCH(1,1) + regime switching dummies	ML
Cotter (2004)	2	VAR(1)	BEKK(1,1,1)	QML
Fernández and Lafuente (2004)	2	Intercept	GJR-GARCH(1,1)	ML
Hsin (2004)	1	AR(1) + 2 dummies	GARCH(1,1)-M with Zakoian asymmetry	2 stages

Table 1: (Continued)

AUTHOR/S	N	MEAN EQUATION	VARIANCE EQUATION	ESTIMATION
Lafuente and Ruiz (2004)	1	AR(1) + standard deviation New Market	TARCH(p,q) + conditional variance New Market	ML-BHHH
Lee, Rui and Wang (2004)	1	ARMA + 1 dummy + spillover regressors	EGARCH(1,1) + 1 dummy + spillover regressors	2 stages
Tai (2004)	4	Conditional ICAPM	BEKK(1,1,1)-M-GJR	QML
Worthington and Higgs (2004)	9	VAR(1)	BEKK(1,1,1)	ML-BHHH
Alonso and Blanco (2005)	1	VEC(1) + official rate + seasonal dummies	EGARCH(p,q) + seasonal dummies + volatility EONIA	QML
Baele (2005)	2	VAR(1)	CCC-GJR / BEKK-GJR / RS-GARCH	ML, QML
Ewing and Malik (2005)	2	AR(1)	BEKK(1,1,1) / BEKK(1,1,1) + regime switching dummies	QML-BFGS
Fung, Lien, Tse and Tse (2005)	2	VEC(10)	EGARCH(1,1)-t	ML
Kim (2005)	1	MA(q) + day and news from US/Japan dummies	EGARCH(1,1)-M + day, volume and news from US/Japan dummies	QML
Wongswan (2006)	1	AR(1)	GARCH(1,1) + day and macroeconomic news from US/Japan dummies	ML / 2 stages
Pardo and Torró (2007)	2	VEC(3) + holiday dummy	BEKK-GJR	QML

N = Number of variables in the multivariate GARCH; N = 1 univariate GARCH; N = n general multivariate GARCH;
res2 = squared residuals;
BHHH = BHHH algorithm; BFGS = BFGS algorithm;

Table 2: Studies reviewed and methodology applied

AUTHOR/S	VAR TYPE	VARIABLES	SAMPLE	FREQ	DATA	MKT	OVLP	METHODOLOGY	COMMENTS
Abad and Novales (2004)	Interest rates	short, medium and long-term rates (Germany, US, Japan)	1987-1998	Daily	C	D	Partial	GARCH	VT from the very short-term to longer-term interest rates.
Aggarwal, Inclan and Leal (1999)	Indices	16 countries and 4 global indices	1985-1995	Weekly	C (Wednesday)	D-E	Total	GARCH, RS	Examines the events that cause large shifts in volatility. Most events tend to be local. The October 1987 crash is the only global event.
Alaganar and Bhar (2002)	ADRs, Indices, Portfolios	Australia, US	1994-2000	Daily	C-C	D-D	No	MGARCH	Unidirectional information flow from the US market to the Australian market.
Alonso and Blanco (2005)	Interest rates	EONIA, 1-month, 3-months, 1-year	1999-2003	Daily	C	D	Total	GARCH	VT from the EONIA to 1-month and 3-month interest rates.
Aragó, Blasco and Corredor (2000)	Spot-Futures	Spain (IBEX35)	1996-1998	Daily	17h-17h	D	Total	MGARCH	Find bidirectional spillovers, more intense after negative news. VT after big and medium-size news.
Aragó, Corredor and Santamaría (2003)	Spot-Futures	Spain (IBEX35)	1996-1997	Daily	C-C and Mid bid-ask quotes	D	Total	CORR, MGARCH	Reduction of transaction costs leads to significant increase in correlations and VT between markets.
Assoé (2001)	Indices and ER	US, 11 emerging and 5 developed	1989-2000	Weekly	C	D-E	Total	MGARCH	D markets: no VT from ER to stock indices. E markets: VT from ER to indices. High volatility persistence and asymmetry also documented.
Ayuso, Haldane and Restoy (1997)	Interest rates	1-day, 1-month, 3-months, 1-year UK, Germany, France, Spain	1988-1993	Daily	C	D	Total	GARCH	Significant VT effect from overnight to longer term money markets for UK, France and Spain.
Bae and Karolyi (1994)	Indices	US, Japan	1988-1992	Intraday	C-O, O-C	D-D	No	CORR, GARCH	The magnitude and persistence of shocks understated if asymmetry is ignored. Propose the International News Impact Curve.
Baele (2005)	Indices	US, EU, 13 EU countries	1980-2001	Weekly	C	D-D	Total	MGARCH, RS	Decomposes local unexpected returns into a country specific shock, a regional EU shock and a global US shock. VT has increased.
Batra (2004)	Indices	Global, India	1979-2003	Monthly	C	E	Total	GARCH, RS	Volatility in India influenced more by domestic political and economic events rather than by global events.
Bekaert and Harvey (1997)	Indices	12 emerging countries	1969-1975	Monthly	C	E	Total	GARCH	Introduces the World Factor Model, approach that allows the relative importance of world and local information to change through time.
Bera and Kim (2002)	Indices	US, Japan, Germany, UK, France, Italy	1990-1995	Daily	C-C	D-D	Partial	MGARCH	Develop a formal test for constancy of correlation. No constant correlation found in their indices.
Billio and Pelizzon (2003)	Indices	Germany, France, Italy, Spain, UK, World	1988-2001	Weekly	C	D-D	Total	RS	Use a multivariate Switching Regime Beta Model (SRBM). VT has increased after EMU.
Bollerslev (1990)	ER	Germany, France, Italy, Switzerland, UK	1979-1985	Weekly	C (Wednesday)	D-D	Total	MGARCH	Introduce the Constant Conditional Correlation model. VT increases after European Monetary System.
Bollerslev and Engle (1993)	ER	UK, Germany	1980-1985	Daily	C	D-D	Total	MGARCH	Extend the IGARCH concept to the multivariate case. Find co-persistence in the ER analyzed.
Booth, Martikainen and Tse (1997)	Indices	Denmark, Norway, Sweden, Finland	1988-1994	Daily	C-C	D-D	Total	COINT, MGARCH	VT is asymmetric. Significant price and volatility spillovers exist but they are few in number.

Table 2: (Continued)

AUTHOR/S	VAR TYPE	VARIABLES	SAMPLE	FREQ	DATA	MKT	OVLP	METHODOLOGY	COMMENTS
Brooks and Henry (2000)	Indices	US, Japan, Australia	1980-1998	Weekly	C (Thursday)	D-D	No	MGARCH	Tests for the existence of linear and non-linear VT. The size and sign of return innovations are important.
Caporale, Pittis and Spagnolo (2002)	Indices and ER	Indonesia, Japan, South Korea, Thailand	1987-2000	Daily	C-C	D,E	Total	MGARCH	Pre-crisis: stock prices lead ER negatively in J and SK and positively in I and T. Post-crisis: in I and T, bidirectional spillover effects.
Chan, Chin and Karolyi (1991)	Spot-Futures	US	1984-1989	Intraday	Minutes	D	Total	CORR, MGARCH	Bidirectional causal relationship between market volatilities.
Cheung and Ng (1996)	Indices, Spot-Futures	US, Japan	1986	Daily, minutes	C-C	D-D	No/ Total	CORR, GARCH	Develops a test for causality in variance and provides two empirical examples.
Chowdhury and Sarno (2004)	ER	EU, Switzerland, UK, Canada	2000	Intraday	Mid bid-ask quotes	D-D	Partial	SV	ER volatility is very persistent and cross–currency spillovers are small.
Conrad, Gultekin and Kaul (1991)	Portfolios	Small, medium and large firms	1962-1988	Weekly	C (Wednesday)	D	Total	GARCH, MGARCH	VT from large to small firms but not vice versa.
Cotter (2004)	ADRs, Indices	Ireland, US, UK, Germany	1990-2000	Daily	C-C	D-D	Partial/ Total	CORR, COINT, MGARCH	VT to but not from the Irish market. Strongest after the ERM crises and before the euro. ADRs play an important role.
Darbar and Deb (1997)	Indices	Canada, Japan, US, UK	1989-1992	Daily	C-C	D-D	Partial	MGARCH	Decompose the estimated covariance in its permanent and transitory components. Find significant transitory covariance and no null permanent covariance.
De Santis and Gerard (1997)	Indices	G7, Switzerland	1970-1994	Monthly	C	D-D	Total	MGARCH	Test de conditional CAPM and evidence supports its restrictions. Severe market declines are contagious but there are still gains from international diversification.
Edwards and Susmel (2001)	Indices	Mexico, Hong Kong, Chile, Brazil and other	1989-1999	Weekly	C (Thursday)	E	Total	MGARCH, RS	High-volatility episodes are short-lived. Volatility co-movements, mainly among Mercosur countries.
Edwards and Susmel (2003)	Interest rates	Argentina, Brazil, Chile, Hong Kong, Mexico	1990s	Weekly	C	E	Total	GARCH, MGARCH, RS	Find evidence of interest-rate volatility comovements across countries.
Engle (2002)	Indices, ER, Stocks, Bonds	-	Several periods	Daily	-	D	-	MGARCH	A new class of multivariate models called Dynamic Conditional Correlation models is proposed.
Engle, Ito and Lin (1990)	ER	US, Japan, Europe, Pacific	1985-1986	Intraday	C-O, O-C	D-D	No	MGARCH	Provides a test of two hypotheses: heat waves versus meteor showers. Finds evidence supporting the last one.
Engle, Ng and Rothschild (1990)	Treasury bills	TB2-TB12	1964-1985	Monthly	C	D	Total	MGARCH	Introduce the Factor ARCH model.
Engle and Susmel (1993)	Indices	18 major stock markets in the world	1980-1990	Weekly	C (Thursday)	D-D	Total	CORR, MGARCH	Use Engle and Kozicki (1993)'s test for common factors. They suggest the existence of a common regional factor rather than a global one.
Ewing and Malik (2005)	Portfolios	Small and large firms	1988-2001	Weekly	C (Wednesday)	D	Total	MGARCH	Accounting for volatility shifts considerably reduces VT and, in essence, removes spillover effects.
Ewing, Malik and Ozfidan (2002)	Indices	Oil and Natural Gas	1996-1999	Daily	C-C	D	Total	MGARCH	Volatility in natural gas returns is more persistent than volatility in oil returns. VT mainly from gas to oil.
Fernández-Izquierdo and Lafuente (2004)	Indices	12 important stock markets	1997-2001	Daily	C-C	D,E	No/ Partial/ Total	MGARCH	Summarize market dynamics into latent factors/trading areas. Use Engle and Kozicki (1993). VT during Asian crisis.

Table 2: (Continued)

AUTHOR/S	VAR TYPE	VARIABLES	SAMPLE	FREQ	DATA	MKT	OVLP	METHODOLOGY	COMMENTS
Fong and Chng (2000)	Stocks	Singapore	1991-1996	Daily	C-C	D	Total	MGARCH	The rate of information absorption in the conditional variance is faster for foreign shares than for local shares.
Forbes and Rigobon (2002)	Indices	Several countries	Several periods	2 days and other	-	-	-	CORR	Heteroskedasticity biases tests for contagion based on correlation coefficients.
Fratzscher (2002)	Indices	US, Europe and 16 countries	1986-2000	Daily	C-C	D-D	Partial/ Total	MGARCH	More European equity integration since 1996, explained by EMU. Euro area has taken over from the US as the dominant market in Europe.
Fung, Lien, Tse and Tse (2005)	Spot-Futures	Hong Kong	1999-2000	Intraday	C	D	Total	MGARCH	Enhanced contribution of the futures price in both price discovery and VT after changing to electronic trading.
Hamao, Masulis and Ng (1990)	Indices	Japan, UK, US	1985-1988	Intraday	C-O, O-C, C-C	D-D	No	CORR, GARCH	VT from New York to Tokyo, London to Tokyo, and New York to London. No VT in other directions is found for the pre-October 1987 period.
Harvey, Ruiz and Shephard (1994)	ER	UK, Germany, Switzerland, Japan	1981-1985	Daily	C	D-D	-	SV	Sets up a multivariate SV model, discusses its statistical treatment and shows how to capture common movements in volatility.
Hsin (2004)	Indices	10 countries	1990-2001	Daily	C-C	D-D	No/ Partial/ Total	GARCH	Significant VT among major world markets. US is the leading market. Effects of the 1997 Asian crisis.
Illueca and Lafuente (2002)	Indices	15 countries	1995-2001	Daily	C-C	D,E	No/ Partial/ Total	GARCH	Evidence on the factor structure of stock market return and volatility. Causal transmission more intense in terms of volatility.
Isakov and Pérignon (2001)	Indices	US, Switzerland, Japan, UK, Germany, France	1988-1998	Intraday	O-C, C-C	D-D	Partial/ Total	CORR, MGARCH	VT from US, Germany and UK to Switzerland. Significant but weak Swiss influence on other markets.
Ito, Engle and Lin (1992)	ER	US, Japan, Europe, Pacific	1979-1988	Intraday	C-O, O-C	D-D	No	MGARCH	The meteor shower effect is more important and it is due to gradual dissemination of private information and not to policy coordination.
Jimeno (1995)	Indices	Spain, Japan, UK, US	1992-1993	Intraday	C-O, O-C, C-C	D-D	No/ Partial/ Total	CORR	Inverse relationship between increases in volatility and contagion, except for the case Tokyo-Madrid.
Karolyi (1995)	Indices, Portfolios of dually and non-dually listed stocks	US, Canada	1981-1989	Daily	C-C	D-D	Total	MGARCH	Magnitude and persistence of VT depend on how cross-market dynamics are modelled.
Karolyi and Stulz (1996)	ADRs	US, Japan	1988-1992	Intraday	C-O, O-C	D-D	Total	CORR, MGARCH	Comovements increase when absolute returns are high. No effect of macroeconomic news nor shocks in interest rates / ER on correlations.
Kearney and Patton (2000)	ER	Europe, France, Germany, Italy, UK	1979-1997	Daily, Weekly	C (Friday)	D-D	Total	COINT, MGARCH	Temporal aggregation reduces VT. The mark plays a dominant position. Model specification is determinant.
Kim (2005)	Indices	US, Japan, Australia, Hong Kong, Singapore	1991-1999	Intraday	C-O, C-C	D-D	No/ Partial/ Total	GARCH	Important spillovers from US to Asia-Pacific markets but weak and country specific from Japan.

Table 2: (Continued)

AUTHOR/S	VAR TYPE	VARIABLES	SAMPLE	FREQ	DATA	MKT	OVLP	METHODOLOGY	COMMENTS
Kim and Rogers (1995)	Indices	US, Japan, Korea	1985-1992	Intraday	C-O, O-C	D-E	No/ Total	CORR, GARCH	Spillovers have increased after market liberalization.
King, Sentana and Wadhwani (1994)	Indices	16 countries	1970-1988	Monthly	C	D-D	Total	MGARCH	Estimate the variance proportion attributable to observable factors, unobservable factors and the idiosyncratic term. Correlations are determined by unobservable factors.
King and Wadhwani (1990)	Indices	US, UK, Japan	1987-1988	Hourly	-	D-D	No/ Partial/ Total	CORR	Find evidence of contagion in October 1987. Model with regime switches depending on the overlapping. Use a *shadow index*.
Koutmos and Booth (1995)	Indices	US, UK, Japan	1986-1990	Daily	C-C	D-D	No/ Partial	MGARCH	Evidence of asymmetry. VT has increased after October 1987.
Koutmos and Tucker (1996)	Spot-Futures	US	1984-1993	Daily	C-C	D	Total	MGARCH	VT from the Futures to the Spot markets.
Kroner and Ng (1998)	Portfolios	Small and large firms	1962-1988	Weekly	C	D	Total	MGARCH	Introduce the GDC and ADC models and the News Impact Surfaces. Provide several specification tests.
Lafuente (2002)	Spot-Futures	Spain (IBEX35)	1993-1996	Hourly	-	D	Total	MGARCH	Bidirectional causal relationship between market volatilities.
Lafuente and Ruiz (2004)	Indices	Financial, Utilities, Industry and New Market	2000-2001	Intraday	O-C	D	Total	GARCH	VT from the New Market to the other sectors.
Lee, Rui and Wang (2004)	Indices	NASDAQ, CDNX, 5 Asian second board markets	1990-2001	Daily	C-C	D-E	No/ Partial/ Total	GARCH	VT from the NASDAQ to the Asian second board markets.
Lin, Engle and Ito (1994)	Indices	US, Japan	1985-1989	Intraday	C-O, O-C	D-D	No	CORR, GARCH	Propose and estimate a signal extraction model with GARCH processes.
Longin and Solnik (1995)	Indices	US and 6 countries	1960-1990	Monthly	C	D-D	Total	CORR, MGARCH	No constant conditional correlation. Correlation rises in periods of high volatility.
Longin and Solnik (2001)	Indices	US, UK, France, Germany, Japan	1959-1996	Monthly	C	D-D	Total	CORR, MGARCH, RS	Correlation is not related to market volatility but to market trend. Correlation increases in bear markets, but not in bull markets.
Martens and Poon (2001)	Indices	US, UK, France	1990-1998	Daily, Weekly	C-C, 16h-16h, C (Wednesday)	D-D	Partial	CORR, MGARCH	Analyze two non-synchroneity adjustment procedures. Correlations respond to volatility only in the case of large negative returns.
Meneu and Torró (2003)	Spot-Futures	Spain (IBEX35)	1994-2001	Daily	17h-17h	D	Total	MGARCH	Introduce the AVIRF. Spot volatility shocks have much more impact on futures volatility than vice versa.
Miyakoshi (2003)	Indices	US, Japan and 7 Asian countries	1998-2000	Daily	C	D-E	No/ Total	MGARCH	Japan influences more Asian volatility than US. New adverse influence from Asia to Japan.
Ng (2000)	Indices	US, Japan and 6 Pacific-Basin countries	1987-1996	Weekly	C (Friday)	D-E	Total	GARCH, MGARCH	Regional factors (Japan) are more important than world factors (US).
Niarchos, Tse, Wu and Young (1999)	Indices	US, Greece	1993-1997	Daily	C-C	D-E	No	COINT, MGARCH	Uses Engle and Kozicki (1993). Markets not interrelated, either in the short-run or in the long-run.
Pardo and Torró (2007)	Indices	Small and large firms	1990-2002	Weekly	C (Wednesday)	D	Total	MGARCH	Volatility shocks from small firms are important to large firms. The reverse is only true for negative shocks.

Table 2: (Continued)

AUTHOR/S	VAR TYPE	VARIABLES	SAMPLE	FREQ	DATA	MKT	OVLP	METHODOLOGY	COMMENTS
Pascual-Fuster (2000)	Portfolios	US, Japan	1996-1998	Daily	O-C	D-D	No	CORR	Estimates GARCH models for the individual series and correlations between those estimated variances.
Peña (1992)	Indices	Spain, US	1988-1989	Daily	C-C	D-D	Partial	GARCH	Meteor shower effect between both markets' volatilities. Also trading volume and day of the week effects.
Pyun, Lee and Nam (2000)	Portfolios	Small and large firms (Korea)	1990-1994	Weekly	C (Thursday)	E	Total	GARCH	VT from large to small firms more significant than vice versa. Trading volume reduces persistence.
Ramchand and Susmel (1998)	Indices	US, Japan, UK, Germany, Canada	1980-1990	Weekly	C (Thursday)	D-D	Total	CORR, GARCH, MGARCH, RS	Correlations are higher in high variance states.
Scheicher (2001)	Indices	Global, Hungary, Poland, Czech Republic	1995-1997	Daily	C-C	E-E	Partial	CORR, MGARCH	Innovations to volatility have a regional character. Spillovers in returns and not in volatilities.
So, Li and Lam (1997)	Indices	7 countries Asia	1980-1991	Daily	C-C	E-E	Partial	SV	Introduce the Threshold Stochastic Volatility (THSV) model.
Sola, Spagnolo and Spagnolo (2003)	Indices	Thailand, South Korea, Brazil	1980-2001	Quarterly	C	E-E	Total	RS	Proposes a new procedure for analyzing volatility links based on a bivariate Markov switching model.
Susmel (2000)	Indices	US, Canada, Japan, UK, Germany, Australia + 2 global	1980-1991	Weekly	C (Thursday)	D-D	Total	GARCH, MGARCH, RS	ARCH and asymmetric effects are reduced when RS is allowed. It looks for common volatility states.
Susmel and Engle (1994)	Indices	US, UK	1987-1989	Hourly	-	D-D	No	GARCH	Volatility spillovers are minimal and have a duration which lasts an hour or so. Heat wave effects. GARCH-t.
Tai (2004)	ER	Japan, Hong Kong, Singapore, Taiwan	1987-2001	Weekly	C	D,E	Total	MGARCH	Multidirectional VT: Singapore, Japan and Taiwan. Unidirectional VT: from Hong Kong to Singapore and Taiwan (negative shocks).
Tse (1999)	Spot-Futures	US (DJIA)	1997-1998	Minutes	-	D	Total	COINT, MGARCH	Bidirectional spillovers. Futures market volatility spillovers to the stock market more than vice versa.
Tse, Wu and Young (2003)	Indices	US, Poland	1994-2003	Intraday	O-C, C-C	D-E	Partial	COINT, MGARCH	No volatility spillover.
Wang, Rui and Firth (2002)	Stocks	Hong Kong, UK	1996-2000	Intraday	C-O, O-C	D-E	No	GARCH	Bidirectional volatility spillovers.
Wongswan (2006)	Indices	US, Japan, Korea, Thailand	1995-2000	Daily, 15min	O-C	D-E	Partial	GARCH, SV	Significant link between D-economy macroeconomic news and E-economy volatility and trade volume.
Worthington and Higgs (2004)	Indices	Hong Kong, Japan, Thailand, Singapore, Indonesia, Korea, Malaysia, Filipinas, Taiwan	1988-2000	Weekly	C	D-E	Partial/ Total	MGARCH	Own-volatility spillovers are generally higher than cross-volatility spillovers, especially for E markets.
Worthington, Kay-Spratley and Higgs (2005)	Spot electricity prices	Five regional electricity markets in Australia	1998-2001	Daily	Daily average	D	Total	MGARCH	Large number of significant own-volatility and cross-volatility spillovers.
Xu and Fung (2002)	ADRs	China, US	1994-2000	Daily	C-C	D-D	No	MGARCH	Mutual feedback. Stocks listed on the offshore market play a bigger role in volatility spillover.
Xu and Fung (2005)	Precious metals futures	US, Japan	1994-2001	Daily	C-O, O-C, C-C	D-D	No	MGARCH	Strong volatility spillover feedback effects and their impacts appear to be comparable and similar.

VAR = Variable; FREQ = Frequency; MKT = Kind of market; OVLP = Overlapping; VT=Volatility Transmission; ER = Exchange Rates;
C = Closing Prices; C-C = Close to Close return; C-O = Close to Open return; O-C = Open to Close return; D = Developed; E = Emerging;
CORR = Cross Correlation; COINT = Cointegration; GARCH = univariate GARCH; MGARCH = multivariate GARCH; RS = Regime Switching; SV = Stochastic Volatility;

CHAPTER 2

Volatility Transmission Patterns and Terrorist Attacks

2.1 Introduction

On September 11, 2001, March 11, 2004 and July 7, 2005, the cities of New York, Madrid and London experienced respectively devastating terrorist attacks. These attacks had an influence over several economic variables and they obviously affected financial markets. Taking into account the increasing global financial integration, an important question arises: How did these terrorist attacks affect interrelations between financial markets?

The main objective of this study is to analyze how volatility transmission patterns are affected by stock market crises. Moreover, we compare the different reactions of the markets to the particular terrorist attacks considered. In order to do this, we use a multivariate GARCH model and take into account both the asymmetric volatility phenomenon and the non-synchronous trading problem. In our empirical application, we focus on stock market crises as a result of terrorist attacks and analyze international volatility transmission between the US and Eurozone financial markets.

It must be highlighted that most existing studies on spillovers between developed countries focus on individual countries such as US, Canada, Japan, UK, France and Germany[1]. As far as we know, there are no many articles analyzing volatility transmission patterns between the US and the Eurozone as a global market. Moreover, this study will be the first one to take into account the non-synchronous trading problem and to use a sample period that includes the September 11, March 11 and July 7 terrorist attacks.

As far as we know, no paper has analyzed until now the effects of the attacks of March 11 and July 7. Moreover, few studies have examined the effects of the attacks of September 11 on financial markets and they focus on the economy as a whole[2] or in

[1] See Koutmous and Booth (1995), Karolyi (1995), Karolyi and Stulz (1996), Darbar and Deb (1997), Ramchand and Susmel (1998), Brooks and Henry (2000), Longin and Solnik (2001), Martens and Poon (2001) and Bera and Kim (2002), *inter alia*.

[2] A special issue of the *Economic Policy Review* of the Federal Reserve Bank of New York (2002, Volume 8, Number 2) analyzes general economic consequences of September 11. A special issue of the *Journal of Risk and Uncertainty* (2003, Volume 26, Numbers 2/3) deals with the risks of terrorism with a special focus on September 11. A special issue of the *European Journal of Political Economy* (2004, Volume 20, Issue 2) deals with the economic consequences of terror.

different concrete aspects of the economy. For instance, Poteshman (2006) analyzes whether there was unusual option market activity prior to the terrorist attacks. Ito and Lee (2005) and Blunk *et al*. (2006) assess the impact of the September 11 attack on US airline demand. Glaser and Weber (2006) focus on how the terrorist attack influenced expected returns and volatility forecasts of individual investors. Chen and Siems (2004) investigate if terrorist and military attacks (including the September 11 attack) are associated with significant negative abnormal returns in global capital markets. Finally, Choudhry (2005) investigates the effects of the September 11 attack and the period after it on the time-varying beta of a few companies in the US. However, none of them analyzes volatility transmission patterns and how they have been affected by the event. As far as we know, the only papers that analyze changes in interrelations between stock markets are Hon *et al.* (2004) and Mun (2005), but they test whether the terrorist attack resulted in a change in correlation across global financial markets. We try to answer the following question: Were there differences in the reaction of the US and Eurozone stock markets to the different terrorist attacks considered? In order to do so, we propose a new version of Asymmetric Volatility Impulse Response Functions (AVIRF) which takes into account stock market crises.

When studying asset price comovements and contagion between different financial markets, an important fact to take into account is the trading hours in each market. In the case of partially overlapping markets (like US and the Eurozone), a jump in prices can be observed in the first market to open when the second one starts trading, reflecting information contained in the opening price. Therefore, this could make volatility increase in this first market. Moreover, as suggested by Hamao *et al.* (1990), a correlation analysis between partially overlapping markets using close to close (C-C) returns could produce false spillovers, both in mean and volatility. This is so because it is difficult to separate effects coming from the foreign market from those coming from the own market while it remains closed.

There are several solutions in order to artificially synchronize international markets. First of all, in the case of US, information transmission with other markets can be analyzed through American Depositary Receipts (ADRs), which will share trading hours with the US market. The problem is that there are no many ADRs, they are not actively traded and there are microstructure differences between the North American stock market and that from the original country (see Wongswan (2006)). Some studies, such as Longin and Solnik (1995) and Ramchand and Susmel (1998), use weekly or monthly data in order to avoid the non-synchronous trading problem. However, the use of low frequency data leads to small samples, which is inefficient for multivariate modeling. On the other hand, some studies, such as Hamao *et al.* (1990) and Koutmos and Booth (1995), use daily non-synchronous open-to-close and close-to-open returns. Nevertheless, these studies cannot distinguish volatility spillovers from contemporaneous correlations. Finally, Martens and Poon (2001) use 16:00-to-16:00 synchronous stock market series in order to solve this problem. By doing this, they find a bidirectional spillover between US and France and between US and UK, contrary to previous studies that only found volatility spillovers from US to the other countries.

This study innovates with respect the existing literature in two ways. First, we study volatility transmission between US and the Eurozone using a sample period including the terrorist attacks occurred in New York, Madrid and London. As far as we know, these terrorist attacks have not yet been included in any paper analyzing volatility transmission in international markets. Second, we introduce a new version of Asymmetric Volatility Impulse Response Functions which takes into account stock market crises.

The rest of the chapter is organized as follows. Section 2 presents the data and offers some preliminary analysis. Section 3 deals with the econometric approach and introduces the AVIRF with crises. Section 4 presents the empirical results and, finally, Section 5 summarizes the main results.

2.2 Data

The data consists of simultaneous daily stock market prices recorded at 15:00 GMT time for the US (S&P500 index) and the Eurozone (EuroStoxx50 index). At that time, the European markets are about to close and the US market has just started trading. We use stock market prices recorded at 15:00 GMT time, at the midpoint of the overlapping hours, in order to avoid the use of index prices recorded exactly at the open (US) and close (Eurozone) of trading.

The data is extracted from Visual Chart Group (www.visualchart.com) for the period January 18, 2000 to January 25, 2006. When there are no common trading days due to holidays in one of the markets, the index values recorded on the previous day are used.

Each terrorist attack considered had a different effect on financial markets. If we focus on the September 11 attack, both price indexes reached their minimum level on September 21. In the Eurozone, the EuroStoxx50 fell by 6.7% the day of the attack and between September 11 and September 21 was down 17.9%. The New York Stock Exchange did not open until September 17 and fell by 5.1%. Between that day and September 21, the S&P500 decreased by 12.3%. In contrast with the effects of the September 11, the March 11 terrorist attack affected less both markets. The EuroStoxx50 decreased by 3.1% the day of the attack and, at the end of that month, it had returned to the pre-attack levels. In the same way, the S&P500 suffered a small decline (1.5%) and recovered in less than a month. Finally, the July 7 attack had no effect on the S&P500 and its impact on the EuroStoxx50 was small (1.7%). All in all, the three terrorist attacks affected much less the US market than the Eurozone market.

Table 1 presents some summary statistics on the daily returns, which are defined as log differences of index values. The Jarque-Bera test rejects normality of the returns for both indexes. This is caused mainly by the excess kurtosis, suggesting that any model for equity returns should accommodate this characteristic of equity returns. The ARCH test reveals that returns exhibit conditional heteroskedasticity, while the Ljung-Box test (of twelfth order) indicates significant autocorrelation in both markets in squared returns but not in levels. Fat tails and non-normal distributions are common features of financial data. Finally, both the augmented Dickey Fuller (ADF) and Philips and Perron (PP) tests indicate that both series have a single unit root. Table 2 shows that both series are not cointegrated, being four the optimal lag length following the AIC criterion.

2.3 The Econometric Approach

2.3.1 The model

The econometric model is estimated in a three-step procedure. First, a VAR model is estimated to clean up any autocorrelation behavior. Then, the residuals of the model are orthogonalized. These orthogonalized innovations have the convenient property that they are uncorrelated both across time and across markets. Finally, the orthogonalized innovations will be used as an input to estimate a multivariate asymmetric GARCH model.

In order to take into account the September 11, March 11 and July 7 terrorist attacks, three dummy series are introduced in the conditional mean equations. These dummies equal one the days following the terrorist attacks in New York, Madrid and London respectively until the days where the indexes take their lowest values, and 0 otherwise.

Equation (1) models the mean equation as a VAR(5) process:

$$\begin{aligned} R_{1,t} &= \mu_1 + x_1 S11_t + y_1 M11_t + z_1 J7_t + \sum_{p=1}^{5} d_{11,p} R_{1,t-p} + \sum_{p=1}^{5} d_{12,p} R_{2,t-p} + u_{1,t} \\ R_{2,t} &= \mu_2 + x_2 S11_t + y_2 M11_t + z_2 J7_t + \sum_{p=1}^{5} d_{21,p} R_{1,t-p} + \sum_{p=1}^{5} d_{22,p} R_{2,t-p} + u_{2,t} \end{aligned} \tag{1}$$

where $R_{1,t}$ and $R_{2,t}$ are US and Eurozone returns, respectively, μ_i, x_i, y_i, z_i and $d_{ij,p}$ for $i,j=1,2$ and $p=1,\ldots,5$ are the parameters to be estimated and $S11_t$, $M11_t$ and $J7_t$ are dummy series for the terrorist attacks. Finally, $u_{1,t}$ and $u_{2,t}$ are the non-orthogonal innovations. The VAR lag has been chosen following the AIC criterion.

The innovations $u_{1,t}$ and $u_{2,t}$ are non-orthogonal because, in general, the covariance matrix $\sum = E(u_t u_t^{'})$ is not diagonal. In order to overcome this problem, in a second step, the non-orthogonal innovations ($u_{1,t}$ and $u_{2,t}$) are orthogonalized ($\varepsilon_{1,t}$ and $\varepsilon_{2,t}$). If we choose any matrix M so that $M^{-1} \sum M^{'-1} = I$, then the new innovations:

$$\varepsilon_t = u_t M^{-1} \tag{2}$$

satisfy $E\left(\varepsilon_t \varepsilon_t^{'}\right) = I$. These orthogonalized innovations have the convenient property that they are uncorrelated both across time and across equations. Such a matrix M can be any solution of $MM^{'} = \sum$.

To model the conditional variance-covariance matrix we use an asymmetric version of the BEKK model (Baba *et al.* (1989), Engle and Kroner (1995) and Kroner and Ng (1998)). As done in the mean equations, we introduce dummy series in order to take into account the terrorist attacks.

The compacted form of this model is:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + G'\eta_{t-1}\eta_{t-1}^{'}G + S'\delta_{t-1}\delta_{t-1}^{'}S + M'\xi_{t-1}\xi_{t-1}^{'}M + L'\vartheta_{t-1}\vartheta_{t-1}^{'}L \tag{3}$$

where C, B, A, G, S, M and L are matrices of parameters to be estimated, being C upper-triangular and positive definite and H_t is the conditional variance-covariance matrix in t.

In the bivariate case, the BEKK model is written as follows:

$$\begin{bmatrix} h_{11t} & h_{12t} \\ \cdot & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}^{'} \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}^{'} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ \cdot & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \tag{4}$$

$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^{'} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \cdot & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}^{'} \begin{bmatrix} \eta_{1,t-1}^2 & \eta_{1,t-1}\eta_{2,t-1} \\ \cdot & \eta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} +$$

$$+ \begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix}^{'} \begin{bmatrix} \delta_{1,t-1}^2 & \delta_{1,t-1}\delta_{2,t-1} \\ \cdot & \delta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix} + \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix}^{'} \begin{bmatrix} \xi_{1,t-1}^2 & \xi_{1,t-1}\xi_{2,t-1} \\ \cdot & \xi_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix} +$$

$$+ \begin{bmatrix} l_{11} & l_{12} \\ l_{21} & l_{22} \end{bmatrix}^{'} \begin{bmatrix} \vartheta_{1,t-1}^2 & \vartheta_{1,t-1}\vartheta_{2,t-1} \\ \cdot & \vartheta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} l_{11} & l_{12} \\ l_{21} & l_{22} \end{bmatrix}$$

where $c_{i,j}, b_{i,j}, a_{i,j}, g_{i,j}, s_{i,j}, m_{i,j}$ and $l_{i,j}$ for all *i,j=1,2* are parameters, $\varepsilon_{1,t}$ and $\varepsilon_{2.t}$ are the unexpected shock series coming from Equation (2), $\eta_{1,t} = \max[0, -\varepsilon_{1,t}]$ and $\eta_{2,t} = \max[0, -\varepsilon_{2,t}]$ are the Glosten *et al.* (1993) dummy series collecting a negative asymmetry from the shocks and, finally, $h_{ij,t}$ for all *i,j=1*, are the conditional second moment series. Similarly to $\eta_{i,t}$, the variables $\delta_{i,t}$, $\xi_{i,t}$ and $\vartheta_{i,t}$ for all *i=1,2* are the dummy series for the terrorist attacks. They take the values of the shocks the days following the terrorist attacks in New York, Madrid and London respectively, until the days where the indexes take their lowest values and 0 otherwise.

Equation (4) allows for both own-market and cross-market influences in the conditional variance, therefore allowing the analysis of volatility spillovers between both markets. Moreover, the BEKK model guarantees by construction that the variance-covariance matrix will be positive definite.

In Equation (4), parameters $c_{i,j}, b_{i,j}, a_{i,j}, g_{i,j}, s_{i,j}, m_{i,j}$ and $l_{i,j}$ for all *i,j=1,2* can not be interpreted individually. Instead, we have to interpret the non-linear functions of the parameters which form the intercept terms and the coefficients of the lagged variances, covariances and error terms. We follow Kearney and Patton (2000) and calculate the expected value and the standard error of those non-linear functions. The expected value of a non-linear function of random variables is calculated as the function of the expected value of the variables, if the estimated variables are unbiased. In order to calculate the standard errors of the function, a first-order Taylor approximation is used. This linearizes the function by using the variance-covariance matrix of the parameters as well as the mean and standard error vectors.

The parameters of the bivariate BEKK system are estimated by maximizing the conditional log-likelihood function:

$$L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left|H_t(\theta)\right| + \varepsilon_t' H_t^{-1}(\theta)\varepsilon_t\right)$$

where T is the number of observations, N is the number of variables in the system and θ denotes the vector of all the parameters to be estimated. Numerical maximization techniques were used to maximize this non-linear log likelihood function based on the BFGS algorithm.

In order to estimate the model in Equations (1) and (3), it is assumed that the vector of innovations is conditionally normal and a quasi-maximum likelihood method is applied. Bollerslev and Wooldridge (1992) show that the standard errors calculated using this method are robust even when the normality assumption is violated.

2.3.2 Asymmetric Volatility Impulse Response Functions (AVIRF) with crisis

The Volatility Impulse-Response Function (VIRF), proposed by Lin (1997), is a useful methodology for obtaining information on the second moment interaction between related markets. The VIRF, AVIRF and our proposed crisis version, measure the impact of an unexpected shock on the predicted volatility. This is:

$$R_{s,3} = \frac{\partial vechE\left[H_{t+s} \mid \psi_t\right]}{\partial dg(\varepsilon_t \varepsilon'_t)} \tag{5}$$

where $R_{s,3}$ is a 3x2 matrix, $s = 1,2,...$ is the lead indicator for the conditioning expectation operator, H_t is the 2x2 conditional covariance matrix, $\partial dg(\varepsilon_t \varepsilon'_t) = (\varepsilon^2{}_{1,t}, \varepsilon^2{}_{2,t})'$ and ψ_t is the set of conditioning information. The *vech* operator transforms a symmetric *NxN* matrix into a vector by stacking each column of the matrix underneath the other and eliminating all supradiagonal elements.

In volatility symmetric structures, it is not necessary to distinguish between positive and negative shocks, but with asymmetric structures the VIRF can change with the sign of the shock. The asymmetric VIRF (AVIRF) for the asymmetric BEKK model is introduced in Meneu and Torró (2003). Similarly, it would be interesting to distinguish between periods of relative stability and periods of financial distress. Therefore, in this chapter we introduce a version of the AVIRF which takes into account periods of stock market crisis. By applying (5) to (3), we obtain:

$$R^{+}_{s,3} = \begin{cases} a & s = 1 \\ (a + b + 1/2g + \alpha w)R^{+}_{s-1,3} & s > 1 \end{cases} \tag{6}$$

$$R^{-}_{s,3} = \begin{cases} a + g & s = 1 \\ (a + b + 1/2g + \alpha w)R^{-}_{s-1,3} & s > 1 \end{cases} \tag{7}$$

$$R^{+,c}_{s,3} = \begin{cases} a + w & s = 1 \\ (a + b + 1/2g + \alpha w)R^{+}_{s-1,3} & s > 1 \end{cases} \tag{8}$$

$$R^{-,c}_{s,3} = \begin{cases} a + g + w & s = 1 \\ (a + b + 1/2g + \alpha w)R^{-}_{s-1,3} & s > 1 \end{cases} \tag{9}$$

where $R^{+}_{s,3}(R^{-}_{s,3})$ represents the VIRF for positive (negative) initial shocks in periods of stability, $R^{+,c}_{s,3}(R^{-,c}_{s,3})$ represents the VIRF for positive (negative) initial shocks in periods of stock market crisis, *a, b* and *g* are 3x3 parameter matrices, α is the probability of occurrence of a crisis and *w* is a 3x3 parameter matrix that, in our case, equals *s*, *m* and *l* during the September 11, March 11 and July 7 terrorist attacks, respectively. Moreover, $a = D^{+}_{N}(A'\otimes A')D_N$, $b = D^{+}_{N}(B'\otimes B')D_N$, $g = D^{+}_{N}(G'\otimes G')D_N$ and $w = D^{+}_{N}(W'\otimes W')D_N$, where D_N is a duplication matrix, D^{+}_{N} is its Moore-Penrose inverse and $\otimes$ denotes the Kronecker product between matrices, that is:

$$D_N = \begin{bmatrix} 1\,0\,0 \\ 0\,1\,0 \\ 0\,1\,0 \\ 0\,0\,1 \end{bmatrix} \qquad D^{+}_{N} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

It is important to note that this impulse response function examines how fast asset prices can incorporate new information. This fact lets us test for the speed of adjustment, analyze the dependence of volatilities across the returns of the S&P500 and the EusoStoxx50, distinguish between negative and positive shocks and distinguish between crisis periods and non-crisis periods.

2.4 Empirical Results

2.4.1 Model estimation

Table 3 displays the estimated BEKK model of Equation (3). In order to keep an appropriate length of the dissertation the results of the estimated VAR(5) are not included, although they are available upon request. The low p-values obtained for most of the parameters show that the model fits well the data. Table 4 shows the standardized residuals analysis. It can be observed that the standardized residuals appear free from serial correlation and heteroskedasticity.

As it has been mentioned above, the parameters of Table 3 can not be interpreted individually. Instead, we have to focus on the non-linear functions that form the intercept terms and the coefficients of the lagged variance, covariance and error terms. Table 5 displays the expected value and the standard errors of these non-linear functions.

The S&P500 volatility is directly affected by its own volatility $(h_{1,1})$ and by the EuroStoxx50 volatility $(h_{2,2})$. Our findings suggest that the S&P500 volatility is affected by its own shocks (ε_1^2) and the EuroStoxx50 shocks (ε_2^2). Finally, the coefficient for its own asymmetric term (η_1^2) and the EuroStoxx50 asymmetric term are significant (η_2^2), indicating that negative shocks on any market affect more volatility than positive shocks.

The behavior of the EuroStoxx50 volatility does not differ much from that of the S&P500. The EuroStoxx50 volatility is affected by its own volatility $(h_{2,2})$, but not by the S&P500 volatility[3]. Interestingly, the EuroStoxx50 volatility is affected by the S&P500 shocks (ε_1^2) and its own shocks (ε_2^2). Finally, the coefficient for its own asymmetric term (η_1^2) and the EuroStoxx50 asymmetric term are significant (η_2^2), indicating that negative shocks on any market affect more volatility than positive shocks.

[3] This could be due to the fact that we use prices recorded at 15:00 GMT, when European markets are about to close and the US market has just started trading.

Regarding dummies, from the analysis of the coefficients significance, the most appealing results are: (1) the September 11 terrorist attack had an influence over volatility of both the US and Eurozone markets, although in the case of the Eurozone, the effect was indirectly transmitted through its own shocks. (2) Both the March 11 and July 7 terrorist attacks did not affect the S&P500 volatility. (3) The July 7 terrorist attack in London had an effect over volatility in the Eurozone. However, the March 11 terrorist attack only affected volatility in the Eurozone indirectly through shocks coming from the S&P500.

In general, there is bidirectional volatility transmission between the US and the Eurozone stock markets. However, the terrorist attack occurred in New York in September 11 affected volatility in the Eurozone stock markets but the terrorist attacks occurred in Madrid and London in March 11 and July 7 respectively did not affect volatility in the US market.

2.4.2 Asymmetric Volatility Impulse Response Functions (AVIRF) with crisis

Figures 1 to 5 present the AVIRFs with crisis, computed following Lin (1997) and Meneu and Torró (2003), as explained in Section 2.3.2. Results add evidence in favor of the bidirectional volatility transmission between the US and the Eurozone stock markets and the different impact that the terrorist attacks had on both markets. These graphical representations also allow us to test for the speed of adjustment, analyze the dependence of volatilities across the returns of the S&P500 and the EusoStoxx50, distinguish between negative and positive shocks and distinguish between crisis periods and non-crisis periods.

Figure 1 represents the AVIRF when unexpected shocks are positive and there is a period of financial stability as opposed to stock market crisis periods caused by terrorist attacks. The graphical analysis shows that there exist bidirectional volatility spillovers between the S&P500 and the EuroStoxx50 (about 4% and 1.5% of the shock, respectively, Figures 1B and 1C). Positive shocks in the EuroStoxx50 have a relatively small effect on its own volatility (Figure 1D), whereas past positive shocks in the S&P500 have no effect on current volatility (Figure 1A).

If unexpected shocks are negative and there is a period of financial stability, Figure 2 shows that there are also bidirectional volatility spillovers between the S&P500 and the EuroStoxx50 (Figures 2B and 2C). Negative shocks in the S&P500 have an important effect on its own volatility (Figure 2A). Negative shocks in the EuroStoxx50 also have an important effect on its own volatility (Figure 2D), though they are less important than in the case of the S&P500. It is interesting to note that own positive shocks do not have any effect on S&P500 volatility, whereas own negative shocks have a very significant effect. In all cases, there is evidence of asymmetry: negative socks have a higher effect on volatility than positive shocks. The only exception is the effect of shocks from the S&P500 on the EuroStoxx50, where both kinds of shock have a similar and relatively small impact on volatility.

One of the most appealing contributions of the new version of the AVIRF introduced in this dissertation is that it allows to differentiate between periods of relative financial stability and periods of stock market crisis caused, in this case, by terrorist attacks. Figure 3 represents the AVIRF to negative unexpected shocks during the crisis period produced by the September 11 terrorist attack. Similarly, Figures 4 and 5 represent the AVIRF to negative unexpected shocks during the March 11 and July 7 crisis periods, respectively. In order to interpret these graphs, it is important to compare the figures with those obtained in Figure 2, AVIRF to negative unexpected shocks in a no-crisis period.

In general, the most appealing results are: (1) Conditional variances are more sensitive to negative than to positive shocks; (2) The September 11 terrorist attack (Figure 3) had an influence over volatility of both the US and Eurozone markets, because all figures have increased their initial response to a shock when compared to Figure 2. In the case of the Eurozone, the effect was indirectly transmitted through its own shocks (Figure 3D). (3) Both the March 11 and July 7 terrorist attacks did not affect the S&P500 volatility (Figures 4A, 4B, 5A and 5B are either non-significative or they do not change when compared to Figure 2). (4) The March 11 and July 7 terrorist attacks had an effect over volatility in the Eurozone (Figures 4C, 4D, 5C and 5D). However, the March 11 terrorist attack (Figure 4) only affected volatility in the

Eurozone indirectly through shocks coming from the S&P500 (Figure 4C), as Figure 4D does not change when compared to Figure 2D.

Therefore, these results add evidence in favor of the hypothesis of bidirectional variance causality between the S&P500 and the EuroStoxx50, but also in favor of the hypothesis of different reactions to each particular stock market crisis due to a terrorist attack.

2.5 Conclusion

The main objective of this study is to analyze how volatility transmission patterns are affected by stock market crises. In order to do this, we use a multivariate GARCH model and take into account both the asymmetric volatility phenomenon and the non-synchronous trading problem. In our empirical application, we focus on stock market crises as a result of terrorist attacks and analyze international volatility transmission between the US and Eurozone financial markets.

In particular, an asymmetric VAR-BEKK model is estimated with daily stock market prices recorded at 15:00 GMT time for the US (S&P500 index) and Eurozone (EuroStoxx50 index).

We also introduce a complementary analysis, the Asymmetric Volatility Impulse Response Functions (AVIRF) with crisis, which distinguishes both a) effects coming from a positive shock from those coming from a negative shock, and b) effects coming from periods of stability from those coming from periods of crisis.

The results confirm that there exist asymmetric volatility effects in both markets and that volatility transmission between the US and the Eurozone is bidirectional. The terrorist attack occurred in New York in September 11 affected volatility in the Eurozone stock markets but the terrorist attacks occurred in Madrid and London in March 11 and July 7, respectively, did not affect volatility in the US market.

Based on Johnston and Nedelescu (2006), there are several possible explanations for the differences in stock market reactions to the three terrorist attacks considered. Firstly, the September 11 terrorist attack had a direct impact on several financial markets, such as the aeronautical, tourism, banking or insurance sectors. These sectors were not so badly affected in the case of the other terrorist attacks considered. Secondly, while the attacks in New York were perceived as a global shock, the attacks on Madrid and London were perceived as mostly having a local and regional effect, respectively. Finally, while the events of September 11 occurred in the midst of a global economic downturn, the terrorist attacks in Madrid and London occurred at a time when the world economy was growing strongly.

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Table 1: Summary statistics

	$R_{1,t}$	*p-value*	$R_{2,t}$	*p-value*
Mean	-0.00009		-0.00019	
Variance	0.00013		0.00021	
Skewness	0.11202	[0.0701]	0.00400	[0.9484]
Kurtosis	3.72923	[0.0000]	4.90041	[0.0000]
Bera-Jarque	782.423	[0.0000]	910.341	[0.0000]
Q(12)	23.2728	[0.0255]	28.8222	[0.0041]
$Q^2(12)$	502.408	[0.0000]	842.236	[0.0000]
ARCH(12)	185.035	[0.0000]	255.721	[0.0000]
ADF(4)	-1.87522	[0.3443]	-1.52663	[0.5200]
PP(7)	-1.90664	[0.3295]	-1.53550	[0.5154]

Note: p-values displayed as [.]. $R_{1,t}$ and $R_{2,t}$ represent the log-returns of the S&P500 and the EuroStoxx50 indexes. The Bera-Jarque statistic tests for the normal distribution hypothesis and has an asymptotic distribution $X^2(2)$. Q(12) and $Q^2(12)$ are Ljung-Box tests for twelfth order serial correlation in the returns and squared returns. ARCH(12) is Engle's test for twelfth order ARCH, distributed as $X^2(12)$. The ADF (number of lags) and PP (truncation lag) refer to the Augmented Dickey and Fuller (1981) and Phillips and Perron (1988) unit root tests. Critical value at 5% significance level of Mackinnon (1991) for the ADF and PP tests (process with intercept but without trend) is -2.86.

Table 2: Johansen (1988) tests for cointegration

Lags	Null	$\lambda_{trace}(r)$	Critical Value	$\lambda_{\max}(r)$	Critical Value
4	r = 0	11.81020	20.26184	7.685361	15.89
	r = 1	4.124843	9.16	4.124843	9.16

Note: The lag length is determined using the AIC criterion. λ_{trace} (r) tests the null hypothesis that there are at most r cointegration relationships against the alternative that the number of cointegration vectors is greater than r. λ_{max} (r) tests the null hypothesis that there are r cointegration relationships against the alternative that the number of cointegration vectors is greater than r + 1. Critical values are from Osterwald-Lenum (1992).

Table 3: Estimation results

Multivariate GARCH model estimation

$$C = \begin{bmatrix} \underset{(0.00)}{-0.001006} & \underset{(0.70)}{0.000017} \\ & \underset{(0.00)}{-0.000511} \end{bmatrix} \qquad B = \begin{bmatrix} \underset{(0.00)}{0.950495} & \underset{(0.07)}{0.001525} \\ \underset{(0.00)}{-0.008417} & \underset{(0.00)}{0.967856} \end{bmatrix}$$

$$A = \begin{bmatrix} \underset{(0.00)}{-0.046510} & \underset{(0.00)}{0.118528} \\ \underset{(0.00)}{0.202174} & \underset{(0.00)}{-0.098272} \end{bmatrix} \qquad G = \begin{bmatrix} \underset{(0.00)}{0.295050} & \underset{(0.00)}{0.034440} \\ \underset{(0.00)}{0.105456} & \underset{(0.00)}{0.202836} \end{bmatrix}$$

$$S = \begin{bmatrix} \underset{(0.00)}{0.114195} & \underset{(0.87)}{-0.018969} \\ \underset{(0.00)}{-0.192744} & \underset{(0.00)}{-0.152630} \end{bmatrix} \qquad M = \begin{bmatrix} \underset{(0.43)}{0.042863} & \underset{(0.00)}{0.320945} \\ \underset{(0.23)}{-0.105324} & \underset{(0.69)}{0.043739} \end{bmatrix}$$

$$L = \begin{bmatrix} \underset{(0.29)}{-0.199620} & \underset{(0.00)}{1.307097} \\ \underset{(0.92)}{0.091490} & \underset{(0.00)}{-6.347604} \end{bmatrix}$$

Note: This table shows the estimation of the model defined in Equation (3). P-values appear in brackets. The necessary conditions for the stationarity of the process are satisfied.

Table 4: Summary statistics for the standardized residuals of the model

	$\varepsilon_{1,t} / \sqrt{h_{11,t}}$		$\varepsilon_{2,t} / \sqrt{h_{22,t}}$	
Q(12)	12.41548	[0.41291]	4.36900	[0.97582]
Q²(12)	11.23055	[0.50927]	13.43020	[0.33856]
ARCH(12)	5.903165	[0.92088]	7.484829	[0.82398]

Note: Q(12) and Q²(12) are Ljung-Box tests for twelfth order serial correlation in the standardized residuals and squared residuals. ARCH(12) is Engle's test for twelfth order ARCH, distributed as $\chi^2(12)$. The p-value of these tests are displayed as [.].

Table 5: Results of the linearized multivariate BEKK model

S&P500 conditional variance equation

$$
\begin{array}{llllllllll}
h_{11,t} = 1{,}01\mathrm{x}10^{-6} & +0{,}9034\, h_{11,t-1} & -0{,}0160\, h_{12,t-1} & +7{,}0845\mathrm{x}10^{-5}\, h_{22,t-1} & +0{,}0021\varepsilon^2_{1,t-1} & -0{,}0188\varepsilon_{1,t-1}\varepsilon_{2,t-1} & +0{,}0408\varepsilon^2_{2,t-1} & +0{,}0870\eta^2_{1,t-1} & +0{,}0617\eta_{1,t-1}\eta_{2,t-1} & +0{,}0109\eta^2_{2,t-1}\ + \\
1{,}10\mathrm{x}10^{-7} & 0{,}0036 & 0{,}0019 & 1{,}7103 & 0{,}0005 & 0{,}0024 & 0{,}0031 & 0{,}0043 & 0{,}0069 & 0{,}0021 \\
(9{,}1454) & (244{,}72) & (-8{,}3242) & (4{,}1422) & (3{,}9943) & (-7{,}7722) & (12{,}864) & (19{,}968) & (8{,}8912) & (5{,}1711)
\end{array}
$$

$$
\begin{array}{lllllllll}
+0{,}01419\,\delta^2_{1,t-1} & -0{,}04592\,\delta_{1,t-1}\delta_{2,t-1} & +0{,}0371\,\delta^2_{2,t-1} & +0{,}0018\xi^2_{1,t-1} & -0{,}0090\xi_{1,t-1}\xi_{2,t-1} & +0{,}0112\xi^2_{2,t-1} & +0{,}0398\vartheta^2_{1,t-1} & -0{,}365\vartheta_{1,t-1}\vartheta_{2,t-1} & +0{,}0083\vartheta^2_{2,t-1} \\
0{,}0030 & 0{,}0028 & 0{,}0096 & 0{,}0047 & 0{,}0070 & 0{,}0188 & 0{,}0767 & 0{,}3712 & 0{,}1708 \\
(4{,}6098) & (-16{,}105) & (3{,}8458) & (0{,}3902) & (-1{,}2803) & (0{,}5957) & (0{,}5190) & (-0{,}0983) & (0{,}0489)
\end{array}
$$

EuroStoxx50 conditional variance equation

$$
\begin{array}{llllllllll}
h_{22,t} = 2{,}61x10^{-7} & +2{,}32x10^{-6} h_{11,t-1} & +0{,}0029h_{12,t-1} & +0{,}9387h_{22,t-1} & +0{,}0140\varepsilon^2_{1,t-1} & -0{,}0232\varepsilon_{1,t-1}\varepsilon_{2,t-1} & +0{,}0096\varepsilon^2_{2,t-1} & +0{,}0011\eta^2_{1,t-1} & +0{,}0139\eta_{1,t-1}\eta_{2,t-1} & +0{,}0411\eta^2_{2,t-1}\ + \\
5{,}22x10^{-7} & 2{,}61x10^{-6} & 0{,}0016 & 0{,}0040 & 0{,}0006 & 0{,}0013 & 0{,}0010 & 0{,}0003 & 0{,}00245 & 0{,}0027 \\
(0{,}5005) & (0{,}8897) & (1{,}7836) & (232{,}43) & (21{,}3179) & (-17{,}7817) & (9{,}3201) & (3{,}3495) & (5{,}7023) & (14{,}7990)
\end{array}
$$

$$
\begin{array}{lllllllll}
+0{,}0003\,\delta^2_{1,t-1} & -0{,}0057\,\delta_{1,t-1}\delta_{2,t-1} & +0{,}0232\,\delta^2_{2,t-1} & +0{,}1030\xi^2_{1,t-1} & +0{,}0280\xi_{1,t-1}\xi_{2,t-1} & +0{,}0019\xi^2_{2,t-1} & +1{,}7085\vartheta^2_{1,t-1} & -16{,}5938\vartheta_{1,t-1}\vartheta_{2,t-1} & +40{,}2920\vartheta^2_{2,t-1} \\
0{,}0044 & 0{,}0362 & 0{,}0098 & 0{,}0209 & 0{,}0726 & 0{,}0097 & 0{,}1203 & 1{,}5037 & 4{,}8040 \\
(0{,}0813) & (-0{,}1599) & (2{,}3750) & (4{,}9072) & (0{,}3865) & (0{,}1960) & (14{,}1995) & (-11{,}0350) & (8{,}3871)
\end{array}
$$

Note: h_{11} and h_{22} denote the conditional variance for the S&P500 and EuroStoxx50 return series, respectively. Below the estimated coefficients are the standard errors, with the corresponding t-values given in parentheses.

The expected value is obtained taking expectations to the non-linear functions, therefore involving the estimated variance-covariance matrix of the parameters. In order to calculate the standard errors, the function must be linearized using first order Taylor series expansion. This is sometimes called the “delta method”. When a variable Y is a function of a variable X, i.e., Y =F(X), the delta method allows us to obtain approximate formulation of the variance of Y if: (1) Y is differentiable with respect to X and (2) the variance of X is known. Therefore:

$$V(Y) \approx (\Delta Y)^2 \approx \left(\frac{\partial Y}{\partial X}\right)^2 (\Delta X)^2 \approx \left(\frac{\partial Y}{\partial X}\right)^2 V(X)$$

When a variable Y is a function of variables X and Z in the form of Y = F(X, Z), we can obtain approximate formulation of the variance of Y if: (1) Y is differentiable with respect to X and Z and (2) the variance of X and Z and the covariance between X and Z are known. This is:

$$V(Y) \approx \left(\frac{\partial Y}{\partial X}\right)^2 V(X) + \left(\frac{\partial Y}{\partial Z}\right)^2 V(Z) + 2\left(\frac{\partial Y}{\partial X}\right)\left(\frac{\partial Y}{\partial Z}\right) Cov(X, Z)$$

Once the variances are calculated it is straightforward to calculate the standard errors.

Figure 1A. A positive shock in the S&P500

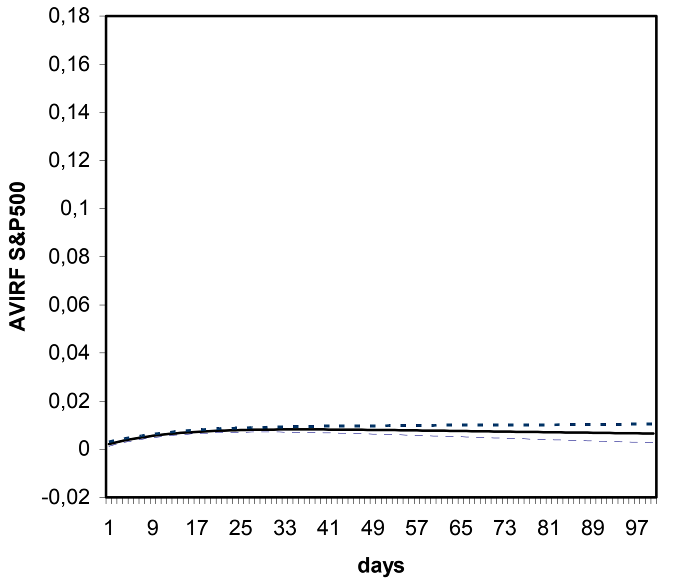

Figure 1B. A positive shock in the EuroStoxx50

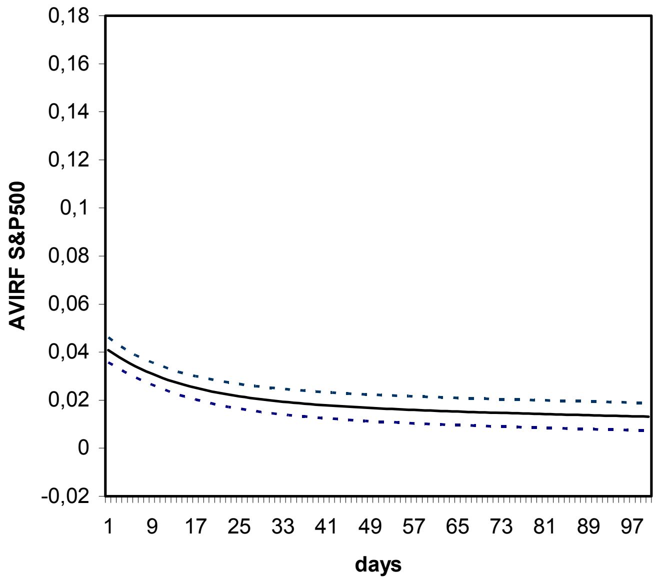

Figure 1C. A positive shock in the S&P500

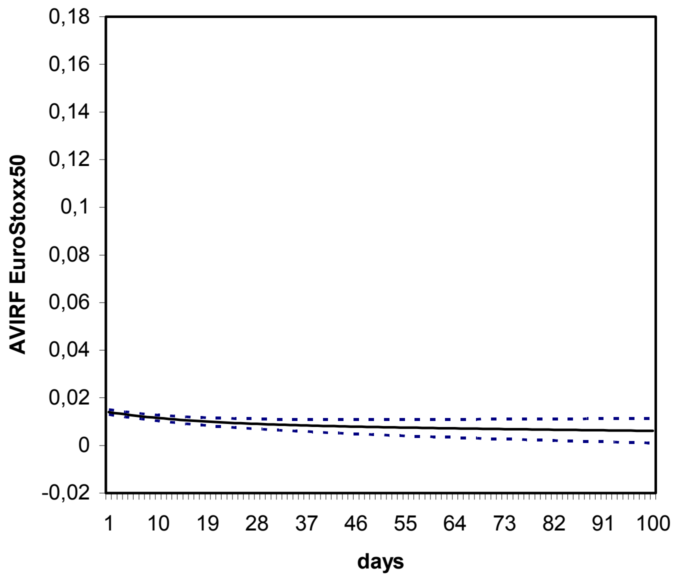

Figure 1D. A positive shock in the EuroStoxx50

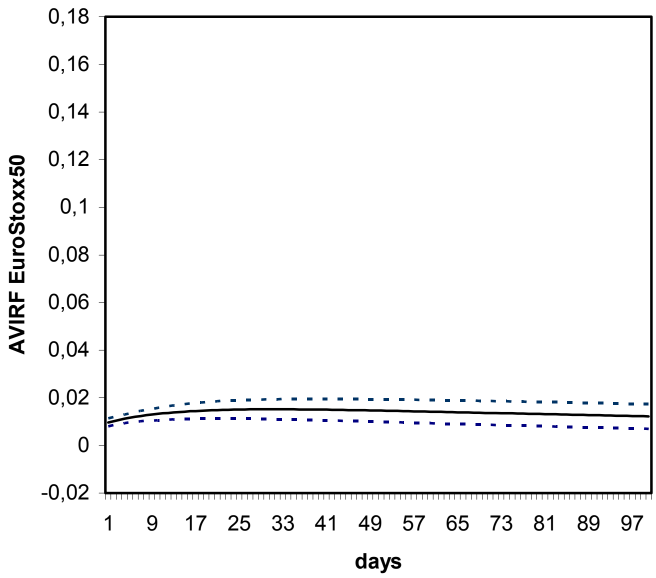

Figure 1: AVIRF to positive unexpected shocks from VAR-Asymmetric BEKK
No Crisis Period
(Dashed lines display the 90% confidence interval)

Figure 2A. A negative shock in the S&P500

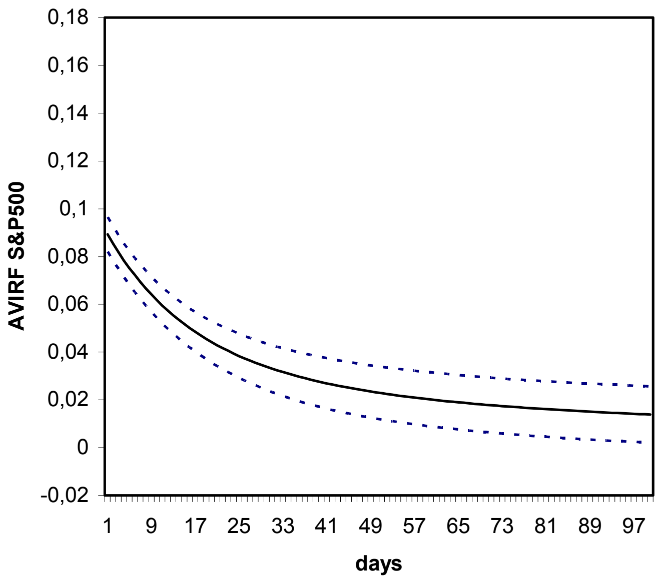

Figure 2B. A negative shock in the EuroStoxx50

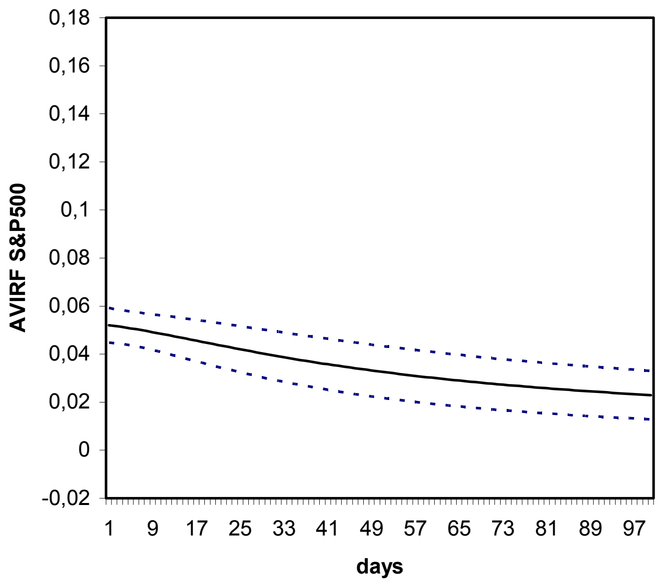

Figure 2C. A negative shock in the S&P500

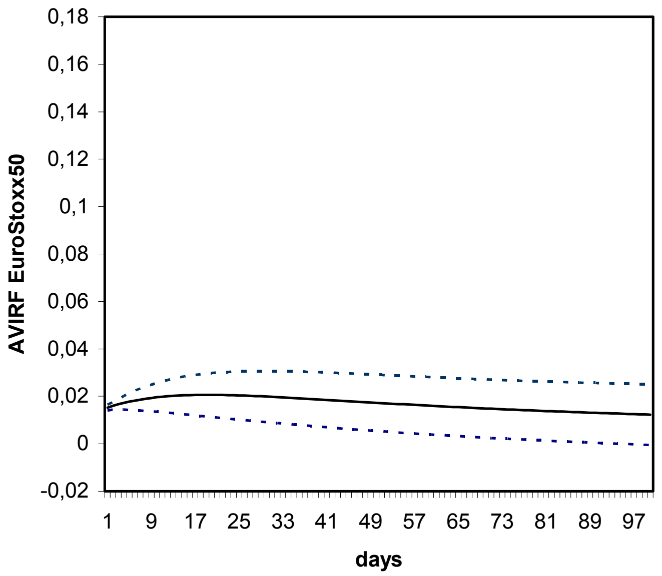

Figure 2D. A negative shock in the EuroStoxx50

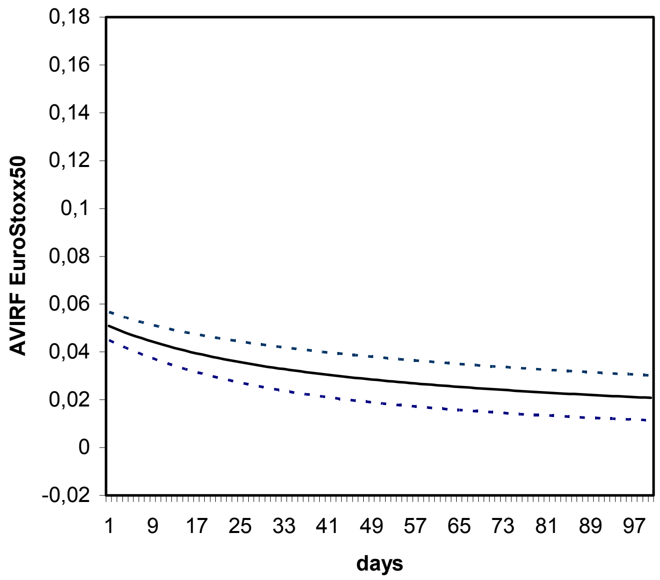

Figure 2: AVIRF to negative unexpected shocks from VAR-Asymmetric BEKK
No Crisis Period
(Dashed lines display the 90% confidence interval)

Figure 3A. A negative shock in the S&P500

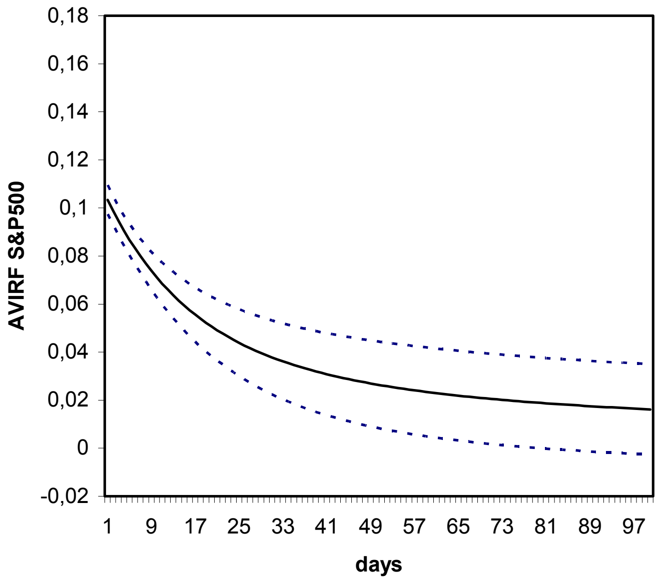

Figure 3B. A negative shock in the EuroStoxx50

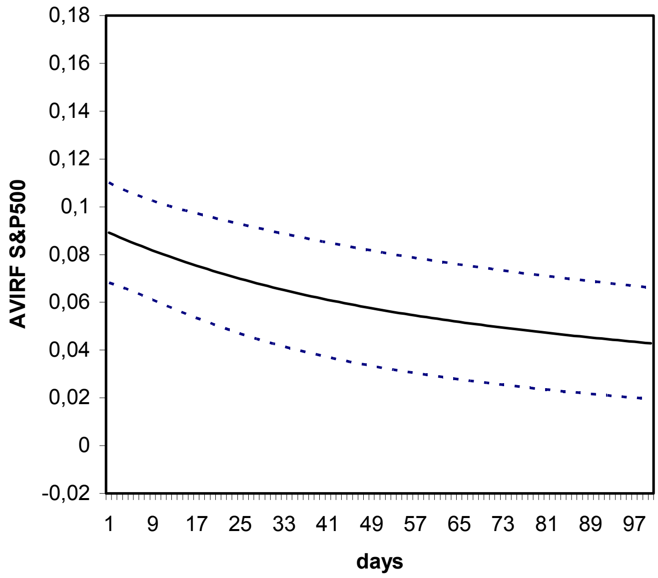

Figure 3C. A negative shock in the S&P500

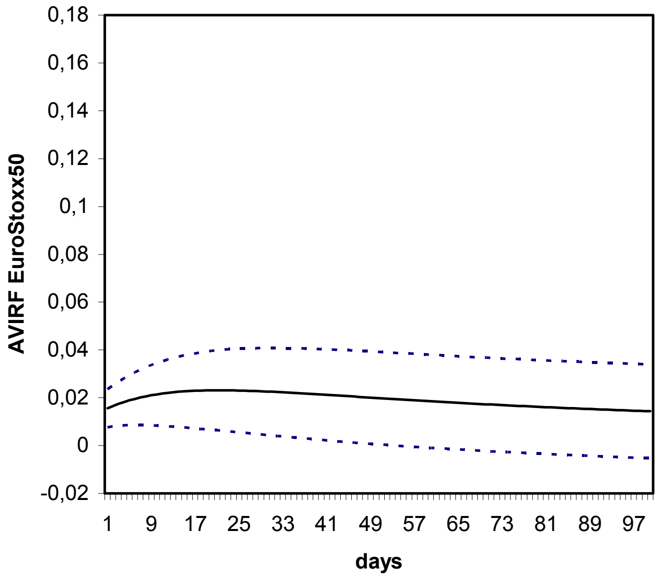

Figure 3D. A negative shock in the EuroStoxx50

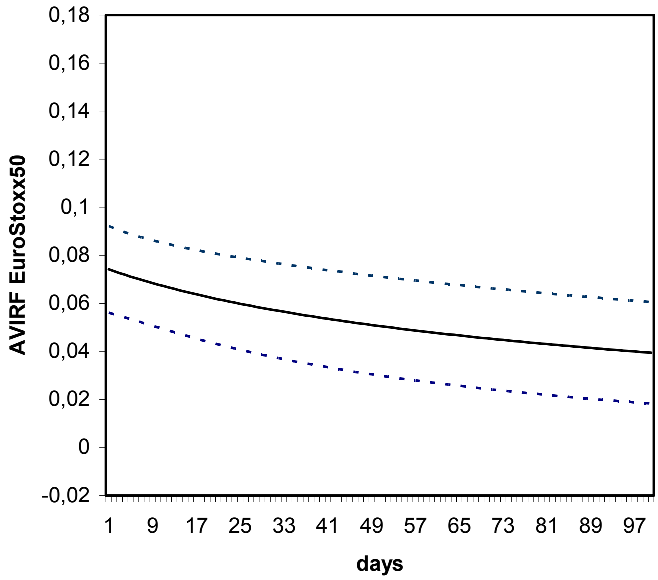

Figure 3: AVIRF to negative unexpected shocks from VAR-Asymmetric BEKK
Crisis Period (September 11)
(Dashed lines display the 90% confidence interval)

Figure 4A. A negative shock in the S&P500

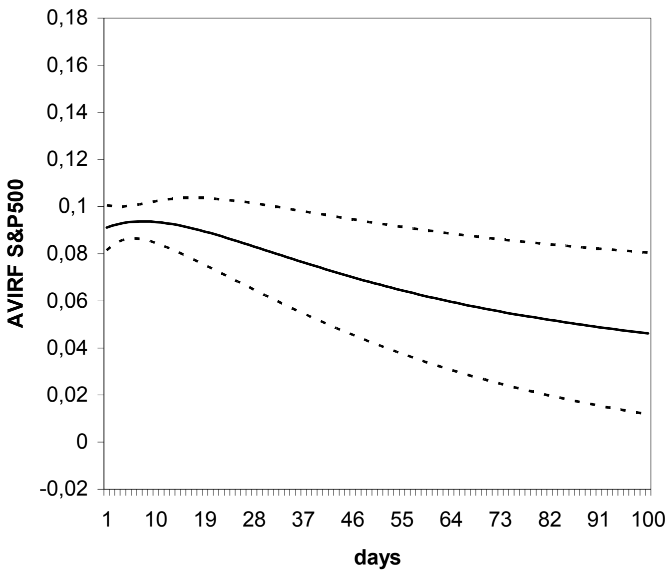

Figure 4B. A negative shock in the EuroStoxx50

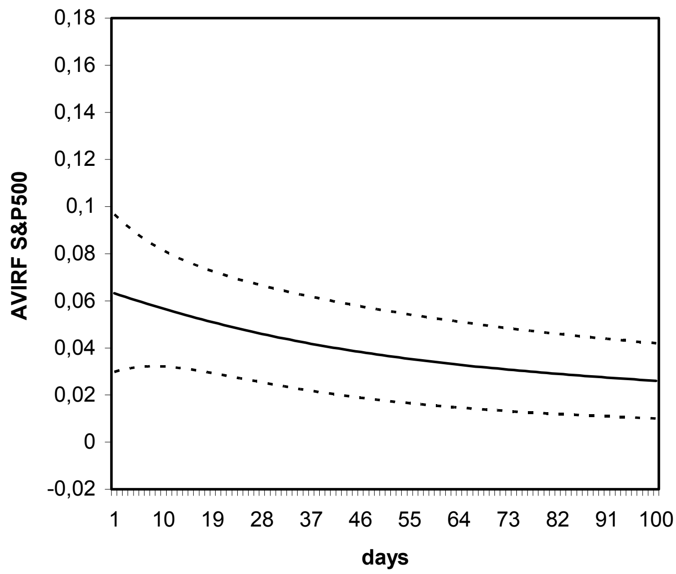

Figure 4C. A negative shock in the S&P500

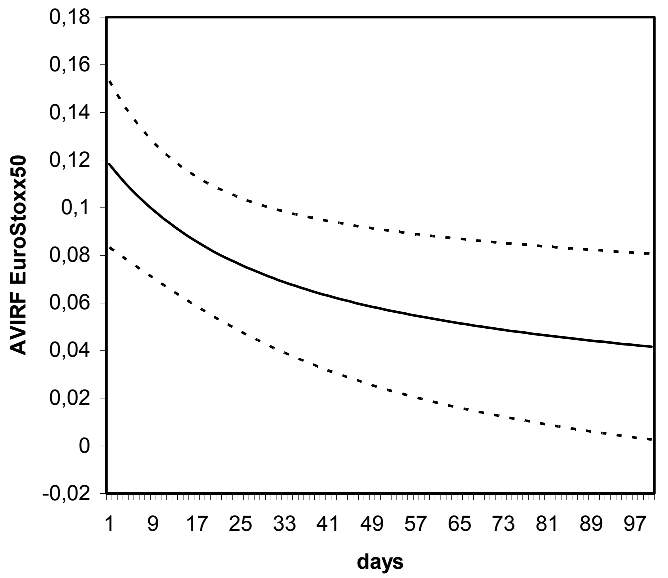

Figure 4D. A negative shock in the EuroStoxx50

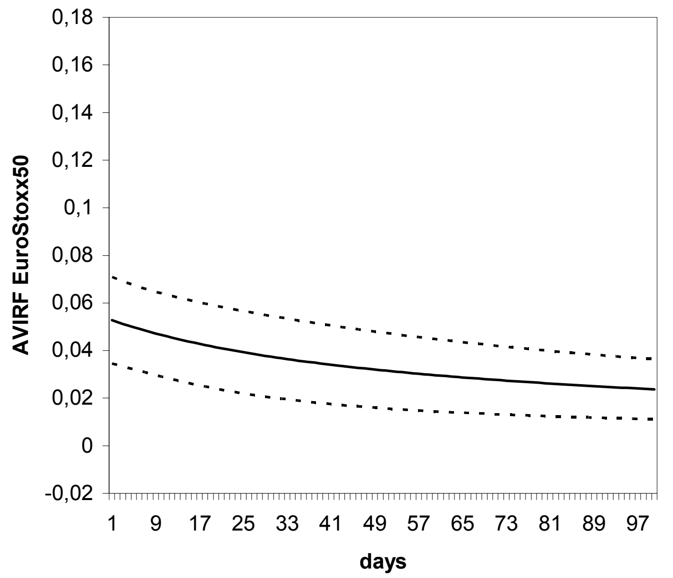

Figure 4: AVIRF to negative unexpected shocks from VAR-Asymmetric BEKK
Crisis Period (March 11)
(Dashed lines display the 90% confidence interval)

Figure 5A. A negative shock in the S&P500

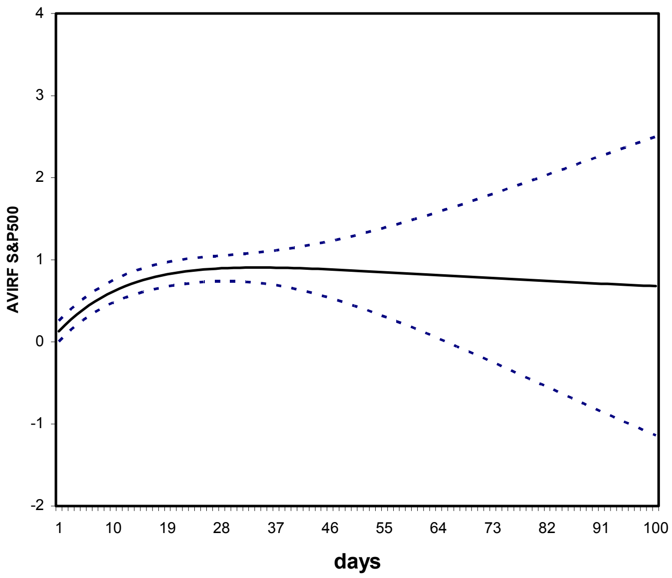

Figure 5B. A negative shock in the EuroStoxx50

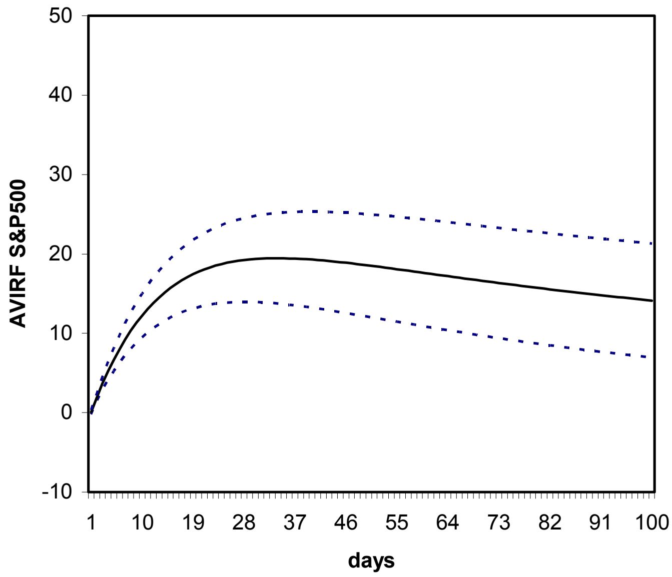

Figure 5C. A negative shock in the S&P500

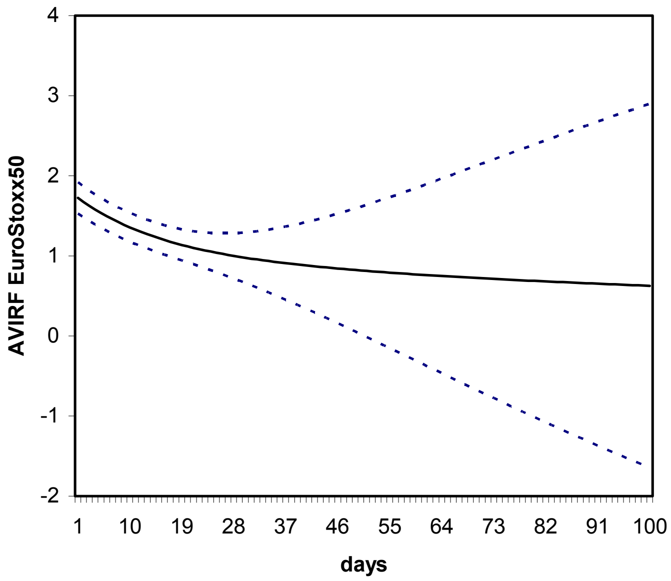

Figure 5D. A negative shock in the EuroStoxx50

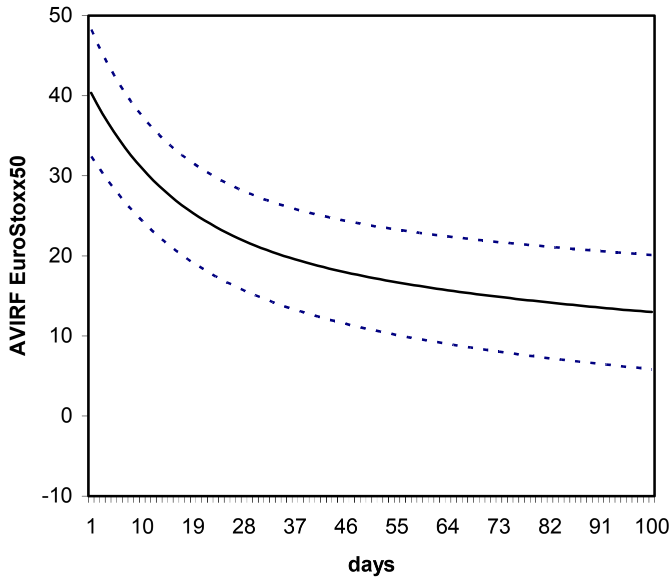

Figure 5: AVIRF to negative unexpected shocks from VAR-Asymmetric BEKK
Crisis Period (July 7)
(Dashed lines display the 90% confidence interval)

CHAPTER 3

Region versus Industry Effects and Volatility Transmission

3.1 Introduction

Whether return variations are driven by national factors or industry factors has long been a challenge to both academics and practitioners. In fact, numerous studies have addressed the question of the relative importance of cross-country versus cross-industry diversification. Appendix A presents a complete literature review in this field. It seems that earlier studies, with samples covering periods up to the late nineties, concluded that country effects dominated industry effects in determining stock returns. More recent works, including in their samples both the late nineties and the early 2000's, showed that industry effects were gaining importance while countries were losing explanatory power. And, finally, the most recent works, with samples covering the recovery from the TMT financial crisis, go back to the dominance of the country effects. This chapter will analyze this trend on a particular way, changing from a country perspective into a regional one.

Obviously, the mixed empirical results in the literature might be due to the different methodologies used, the different countries and industry classification chosen and, surely, the different periods being analyzed. In fact, the mixed results suggest that the importance of country and industry factors may have been changing over time.

Apart from evaluating the relative importance of regional and industry effects, it would be interesting for portfolio managers and policy makers to know whether the same international linkages found in aggregate stock market indices exist at the industry level. This idea, which has not been included in earlier studies analyzing country versus industry effects, could answer several important questions such as: How important are those linkages? Are regional industrial indices related through their second moments? Which industries present a higher level of international interaction?

To our knowledge, few studies have used volatility transmission analysis to better understand information flows within an industry. The issue of volatility transmission is extensively studied in the literature (see Booth *et al*. (1997), Bekaert and Harvey (1997), Kearney and Patton (2000) and Ng (2000), among others), but the major focus has been on either the linkages between stock markets of different countries or different types of markets within a given country. We propose to analyze volatility transmission within an industry across regions through a multivariate GARCH specification. Moreover, we use the asymmetric version of the BEKK model proposed by Engle and Kroner (1995)[1], which allows the entire variance-covariance structure of the model to respond in an asymmetric manner to positive and negative shocks.

Arshanapalli *et al*. (1997) is one of the few studies that analyzes relations within one industry across different regions. They use the common ARCH-feature testing methodology, developed by Engle and Kozicki (1993), to examine the issue of a common volatility process among asset prices of nine industry groups from three economic regions. It is found that industry-return series exhibit intra-industry common time-varying volatility process. The evidence is consistent with the view that world capital markets are related through their second moments implying that a world common time-varying variance specification seems to be appropriate in modeling asset prices. While their empirical evidence suggests that investors can form constant-variance portfolios by investing within an industry across regions, they suggest that investors would be better off if they invested across regions and industries rather than diversify within an industry across different geographical regions.

Therefore, this chapter has two main objectives. First, it analyzes the relative importance of regional versus industrial effects, as opposed to country versus industrial effects, using an enlarged sample (1995-2004) including the period after the bursting of the TMT bubble. Second, it analyzes volatility transmission patterns in a particular industry across different regions.

We seek to contribute to the existing literature in several ways. To our knowledge, this study is the first one to focus on specific regions rather than countries. This idea comes from Brooks and Del Negro (2005), who develop a new decomposition that disaggregates country effects into region effects and within-region country effects. They find that half the return variation typically attributed to country effects is actually due to region effects, a result robust across developed and emerging markets. Complementarily, it analyzes volatility transmission, through multivariate GARCH models, using industrial indices. This analysis provides further information to portfolio

[1] The asymmetric BEKK model is also used by Kroner and Ng (1998), Brooks and Henry (2000), Isakov and Pérignon (2001) and Tai (2004), among others.

managers willing to achieve optimal portfolio diversification. Other studies, such as Berben and Jansen (2005), have analyzed linkages across countries within an industry but they focus their analysis in correlations. Another important difference to other studies is the use of daily data. The vast majority of empirical studies use weekly and monthly data, though portfolio managers are surely interested in the behavior of daily returns. Finally, as it has already been pointed out, this study uses a wide sample (1995-2004) that includes the bursting of the TMT bubble.

The remainder of this chapter is organized as follows. Section 2 describes the data employed in the study. In Section 3, the models used to compare region and industry effects and to analyze volatility spillovers are presented. Section 4 contains the empirical results and, finally, Section 5 provides a brief summary and some concluding remarks.

3.2 Data

The data set consists of daily price indices in US dollars for 10 industry indices in 3 different regions (North America, European Union and Asia), all collected from Datastream International.

The *North America* region covers US and Canada. The *European Union* includes the 15 former EU members from 1995 to 2004 (Germany, Belgium, Denmark, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Sweden and United Kingdom) plus Cyprus, Czech Republic, Hungary and Poland. Finally, China, Sri Lanka, Hong Kong, Indonesia, India, Japan, Korea, Malaysia, Philippine, Pakistan, Singapore, Taiwan and Thailand, all are included in the *Asian* region.

We follow the broad distinction of ten economic industries according to the Level 3 of the FTSE Actuaries classification: Resources, Basic Industries, General Industrials, Cyclical Consumer Goods, Non-cyclical Consumer Goods, Cyclical Services, Non-cyclical Services, Utilities, Information Technology and Financials (see Table 1 for a more detailed description).

Datastream indices target 80% coverage of market capitalization and they provide the widest coverage of developed and emerging market equity returns. In the case of sectoral indices, each of them includes all domestic stocks that belong to that industry/sector. Market capitalization for each of the indices is also obtained from Datastream International.

The sample, from January 2, 1995 to December 31, 2004, includes 2610 observations per index. We have computed daily logarithms rates of returns from the price indices.

Finally, the whole sample is divided into three sub-periods in order to better isolate the Internet bubble and the TMT financial crisis. A graphical analysis of the time series of the Information Technology (IT), Cyclical and Non-cyclical Services industries, in the three regions, pointed at the period from 1998 to 2001 to account for that particular crisis (Figure 1). In particular, from 1998 to the first quarter of 2000 these industrial indices experienced an important increase and, after then, the bursting of the TMT bubble produced a sharp decrease in these indices. From the beginning of 2002, the TMT related industries started their slow recovery.

3.3 Methodology

3.3.1 Region versus industry effects

First of all, we will analyze the relative importance of region and industry effects. In this study, we use the dummy variable approach (introduced by Heston and Rouwenhorst (1994) and extended by Griffin and Karolyi (1998)) that assumes that the return on a given index in a given industry varies due to a common effect (α), a global industry effect (β), a country effect (γ) and a residual index-specific disturbance (ε). In our case, the return of an index *i* of industry *j* and region *k* at time *t* is given by:

$$R_{i,t} = \alpha_t + \beta_{j,t} + \gamma_{k,t} + \varepsilon_{i,t} \quad (1)$$

We estimate the following equation daily for each region and industry index:

$$R_i = \alpha + \beta_1 I_{i1} + \beta_2 I_{i2} + ... + \beta_{10} I_{i10} + \gamma_{NA} RG_{iNA} + \gamma_{EU} RG_{iEU} + \gamma_{AS} RG_{iAS} + \varepsilon_i \qquad (2)$$

where I_{ij} is a dummy variable that equals one if the index belongs to industry *j* and zero otherwise, and RG_{ik} is a similar dummy variable that identifies region affiliation. There are *J=10* industries and *K=3* regions in total.

Since each return belongs to both one region and one industry, there is an identification problem if dummy variables are defined for every region and industry. To avoid the interpretation problem of an arbitrary benchmark, we can impose the constraint that, for value weighted portfolios, the sum of the industry coefficients equals zero and the sum of the region coefficients equals zero. We estimate Equation (2) cross-sectionally for the 10 industry groupings (*I*) in each of the 3 regions (*RG*) subject to the following restrictions:

$$\sum_{j=1}^{10} w_j \beta_j = 0 \qquad (3a)$$

$$\sum_{k=1}^{3} v_k \gamma_k = 0 \qquad (3b)$$

where w_j and v_k denote the value weights of industry *j* and region *k* in the world market portfolio. The least-squares estimate of the intercept in Equation (2) can then represent the return on the value-weighted world market portfolio.

Weighted least squares (WLS) estimates for Equation (2) are computed each day subject to the restrictions in Equations (3a) and (3b). The daily cross-sectional regressions yield a time series of the intercept and the region and industry coefficients. We interpret the estimated beta coefficient ($\hat{\beta}$) as the estimated 'pure' industry effect relative to the return on the value-weighted world market portfolio, and the estimated gamma ($\hat{\gamma}$) as the estimated 'pure' region effect relative to the return on the value-weighted world market portfolio. The time series of these coefficients reveals whether region or industry effects have greater variation.

We follow the literature in computing the estimated variances of the industry and region effects. From Equation (2), the excess returns over the benchmark world portfolio can be decomposed into the weighted sum of industry and region effects. The higher the variance of industry (region) effects, the higher the proportion of the variability in excess returns explained by industry (region) factors. More intuitively, if the variability of industry effects is higher than that of region effects, more risk reduction will be achieved by diversifying across industries than by diversifying across regions.

3.3.2 Volatility transmission

The econometric model used to analyze interrelations within an industry across different regions has to parts: the mean equation and the variance-covariance equation.

Equation (4) models the index returns in a particular industry i as a first order Vector Autoregressive VAR(1) process[2]. Using matrix algebra:

$$\begin{bmatrix} R_{1,t} \\ R_{2,t} \\ R_{3,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} \begin{bmatrix} R_{1,t-1} \\ R_{2,t-1} \\ R_{3,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix} \tag{4}$$

where R_t is the vector of daily returns in the three regions at time t, μ is a vector of constants, ε_t is a vector of innovations and D is a 3x3 matrix of parameters.

Equation (4) describes the index returns of the North America ($R_{1,t}$), European Union ($R_{2,t}$) and Asia ($R_{3,t}$) markets as a VAR(1) process where the conditional mean in each market is a function of a constant, past own returns and the other two markets' past returns. The coefficients in D measure those own and cross-effects. For instance, d_{21} is the effect of a unit change in $R_{1,t-1}$ on $R_{2,t}$. From the mean equation we get the residuals that will be used as input in the variance-covariance equation.

Numerous evidence indicates that stock returns exhibit ARCH effects and that

[2] Lag order selection is based on the AIC criterion.

international stock markets are related both at the mean and the variance level. It is reasonable to assume that the same characteristics could hold for industry-level data. We therefore employ a *Generalized Autorregressive Conditional Heteroskedasticity* (GARCH) model to analyze volatility transmission patterns within a particular industry in different regions.

As we are interested in the interrelationship between different industrial indices, a multivariate GARCH framework is necessary. Different multivariate GARCH specifications have been proposed in the literature. The four multivariate GARCH models mostly used in the literature are the VECH, Diagonal, Constant Conditional Correlation (CCC) and BEKK models. Each one of them imposes different restrictions in the conditional variance. In the VECH model (Bollerslev *et al*. (1988)), certain restrictions must be accomplished in order to assure a positive definite variance-covariance matrix. The Diagonal representation (Bollerslev *et al*. (1988)) reduces the number of parameters to be estimated, but it also removes the potential interactions in the variances of different markets. Bollerslev (1990) proposes a model with constant correlations between markets. However, different studies (see, Longin and Solnik (1995)) have shown that this assumption is violated in international markets. Finally, the BEKK model (Engle and Kroner (1995)) is the specification that best fits our objectives. The main advantage of this specification is that it reduces significantly the number of parameters to be estimated without imposing strong constraints on the shape of the interaction between markets. Moreover, it guarantees that the variance-covariance matrix will be positive definite.

In the BEKK specification, an asymmetry term can be easily introduced. The most common case of volatility asymmetry in stock markets is the negative one, where unexpected falls in prices cause greater volatility than unexpected increases in prices of the same amount. The importance of modeling the asymmetric effect comes from the need of obtaining better model fits. As suggested by several authors, conclusions obtained from volatility transmission models could be erroneous when asymmetries are not modeled (Susmel and Engle (1994) and Bae and Karolyi (1994)).

Therefore, our variance-covariance matrix will follow the BEKK model proposed by Engle and Kroner (1995) and, following Glosten *et al*. (1993), we will capture asymmetry in the variance-covariance structure using a threshold term in the variance. The whole compacted model is written as follows:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + G'\eta_{t-1}\eta_{t-1}^{'}G \qquad (5)$$

where C, B, A and G are 3x3 matrices of parameters, being C upper triangular[3], H_t is the 3x3 conditional variance-covariance matrix, ε_t is a 3x1 vector containing the unexpected shocks obtained from Equation (4) and η_t is a 3x1 vector containing the threshold terms, where $\eta_{kt} = \max[0, -\varepsilon_{kt}]$ and $k = 1,2,3$. This asymmetric BEKK specification requires estimation of 33 parameters.

The B matrix depicts the extent to which current levels of conditional variances are related to past conditional variances. Similarly, the elements in A capture the effects of lagged shocks or events on current volatility. Finally, the elements in G indicate whether volatility spillovers depend upon not only the size, but also the sign of the innovation in returns.

The expanded version of the conditional variance for each region can be found in Appendix B. In the variance equations, the elements in C, B, A and G can not be interpreted individually. Instead, we have to interpret the non-linear functions of the parameters which form the intercept terms and the coefficients of the lagged variances, covariances and error terms[4].

3.4 Empirical Results

3.4.1 Region versus industry effects

First, to determine the relative importance of region and industry effects, we examine the amount of variation explained by the time series of estimated region and

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[3] C is restricted to be upper triangular in order to guarantee a positive definite *Ht*. See Engle and Kroner (1995) for further details.

[4] We follow Kearney and Patton (2000) and calculate the expected value and the standard error of those non-linear functions. The expected value of a non-linear function of random variables is calculated as the function of the expected value of the variables, if the estimated variables are unbiased. In order to calculate the standard errors of the function, a first-order Taylor approximation is used. This linearizes the function by using the variance-covariance matrix of the parameters as well as the mean and standard error vectors.

industry coefficients. Thus, we computed variance for the pure region and industry effect over time. Table 2 shows the results for the full sample period, from January 1995 to December 2004, and for the sub-periods analyzed.

The pure region effects indicate that Asia exhibited the most variation in all periods. This result suggests that Asia is the market most segmented from the other markets and, conversely, North America and the European Union are closer to each other. The Asian region includes several emerging markets, and country effects in these markets are on average much more variable than in mature markets (see Brooks and Del Negro (2004)). On the other hand, North America exhibited the least variation in all periods. This is not surprising since the region is composed by only two mature markets (US and Canada).

The resources industry has the largest variance of pure industry effects. In fact, resources, information technology and utilities account for three of the largest variances shown in Table 2 in all the periods analyzed. This is consistent with the findings of Heckman *et al*. (2001), who undertook a study on the relative importance of countries and industries in determining European company returns for the period 1989 to 2000. At the sector level, technology, energy, telecommunication services, utilities, and financial conglomerates were found to have the largest industry effects. Similarly, Ferreira and Ferreira (2006) found the largest variances in the resources and information technology industries in their study of the EMU equity markets.

When we compare the average variance of the region effects to the average variance of the industry effects, we find a ratio of approximately 1:1 when we analyze the full sample period. Region effects are more important at the beginning (1995-1997) and at the end (2002-2004) of the total period. However, in the middle of the sample the importance of industry effects rises dramatically and surpasses that of region effects: for the 1998-2001 period the ratio of country to industry variances is about 3:4. Brooks and Del Negro (2004) find a similar result using the same sub-sample, though they report a ratio of 1:2. Therefore, the sub-periods analysis suggests that, although industry effects dominated region effects during the TMT financial crisis, region effects continue to be the most important determinant of variation in international returns. In fact, in the most current sub-period, the ratio of region effects to industry effects is about 2:1.

3.4.2 Volatility transmission

In order to analyze volatility transmission patterns *within* an industry *across* regions, the trivariate model in Equations (4) and (5) is estimated for each of the 10 industries, following a two-step procedure[5]. First, the VAR(1) model is estimated by Ordinary Least Squares (OLS) applied equation by equation. Second, the Bollerslev and Wooldridge (1992) Quasi-Maximum Likelihood (QML) estimator is used to obtain robust estimates of the asymmetric BEKK model. Estimation results for each of the ten industries can be found in Appendix C.

The residual diagnostics indicate that the VAR(1) - asymmetric BEKK model obtains a good fit in all industries analyzed[6]. In general, the Ljung–Box Q statistics show no evidence of autocorrelation in the standardized residuals and squared residuals. Following Worthington and Higgs (2004), given that 26 of the 30 conditional expected return equations provide an adequate description of the data, we can conclude that the conditional mean and variance return equations are correctly specified.

The analysis of coefficient significance in the mean equation appears to support the hypothesis that events in North America cause events in the European Union and Asia, with evidence of feedback only in a couple of industries. The same conclusion applies to mean spillovers from the European Union to Asia.

The significance of the off-diagonal elements in A, B and G is also suggestive of spillovers in variance, more or less important depending on the industry being analyzed. In particular, the almost general significance of the parameters in the G matrix suggests that the volatility spillovers depend not only on the size, but also on the sign of the innovations in returns. Thus, there exist asymmetric effects in the volatility transmission patterns analyzed.

The significance of the off-diagonal elements in A and B also suggests that Asia is the market relatively most isolated from the other markets, with 1/5 of the off-diagonal estimated parameters non significant. This ratio is lower in the case of the European

[5] See Kroner and Ng (1998) and Tse (1999).
[6] Residual diagnostics are available upon request.

Union and North America. Similarly, Berben and Jansen (2005), who analyze correlations in US, UK and Japan, find that correlations with respect to Japan are low, suggesting that the Asian market is comparatively disconnected from the others. In contrast, the US and UK markets exhibit a much higher degree of comovement.

In general, in all industries, the diagonal transmission coefficients in A and B are statistically significant, giving evidence of the existence of own GARCH effects in the data. The industries with more interaction between their second moments are Basic Industries and General Industrials. In contrast, the Information Technology industry is the less affected by other international markets. These results are also in accordance with the evidence found in Berben and Jansen (2005) when analyzing correlations within an industry across countries. As suggested by them, the combination of low correlation, high volatility and low degree of international interdependence, could indicate that it is region or country-specific industry shocks that drive the returns of IT shocks.

As it has been mentioned above, the estimated parameters should not be interpreted individually. Instead, we should focus on the non-linear functions that form the intercept terms and the coefficients of the lagged variance, covariance and error terms. As an example, Table 3 displays the expected value, the standard errors and the t-statistics of these non-linear functions for the Information Technology industry[7]. Statistically significant coefficients measure the effect of a unit change in the regressor on volatility. For instance, for the North American conditional variance equation, 0.0358 would be the effect of a unit change in past volatility ($h_{11,t-1}$) on current volatility ($h_{11,t}$).

Table 3 indicates that volatility in the North American region is directly affected by its own past volatility ($h_{11,t-1}$) but not by the European Union ($h_{22,t-1}$) or Asian ($h_{33,t-1}$) volatility. Our findings suggest that the North American volatility is not affected by positive shocks originated in any region, neither directly nor indirectly. However, all coefficients for asymmetric terms, except the one that accompanies $\eta_{3,t-1}^2$, are significant, indicating that negative shocks do have an effect on volatility, except those

[7] In order to keep an appropriate length of the dissertation, tables for the rest of industries are not included, though they are available upon request.

coming from the Asian region.

Volatility in the European Union IT industry is also only affected by its own past volatility ($h_{22,t-1}$). However, in this region, there is a negative impact of past covariance between North America and European Union stock returns ($h_{12,t-1}$) on volatility. Interestingly, the European Union volatility is only affected by its own shocks ($\varepsilon^2_{2,t-1}$) and the coefficient for the own asymmetric term ($\eta^2_{2,t-1}$) is significant, indicating that own negative shocks affect more volatility than own positive shocks.

Finally, volatility in the Asian IT industry is affected by own past volatility ($h_{33,t-1}$), own past shocks ($\varepsilon^2_{3,t-1}$) and, indirectly, by shocks coming from North America ($\varepsilon_{1,t-1}\varepsilon_{3,t-1}$).

3.5 Conclusion

This chapter has two main objectives. First, it analyzes the relative importance of regional versus industrial effects, as opposed to the extensively analyzed in the literature country versus industrial effects, using a wide sample including the period after the bursting of the TMT bubble. Second, it analyzes volatility transmission patterns in a particular industry across different regions. This analysis completes the information needed by portfolio managers when deciding in which regions and which industries to invest in order to diversify risks.

The results confirm the overall dominance of regional effects over industry effects. Although our findings over the whole sample time period suggest that both effects have been relatively similar in importance when determining equity returns, the pattern reveals an increasing relative importance of industrial effects only in periods of sectoral booms. In fact, the sub-periods analysis suggests that, although industry effects dominated region effects during the TMT financial crisis, region effects continue to be the most important determinant of variation in international returns. As Brooks and Del Negro (2004), we see this evidence as suggestive that the rise in industry effects was a temporary phenomenon associated with the TMT bubble. The implications of our research for investors are that, once the TMT financial crisis is over, the traditional strategy of diversifying across countries or regions rather than industries may still be adequate in terms of reducing portfolio risk.

Complementarily, in the volatility transmission analysis, the results are suggestive of spillovers within an industry across international regions, more or less important depending on the industry being analyzed. The industries with more interaction between their second moments are Basic Industries and General Industrials. In contrast, the Information Technology industry is the less affected by other international markets. This again suggests that ignoring location aspects in the diversification strategy could be erroneous.

For those practitioners whose current global strategy assumes that global equity markets remain significantly segmented, this chapter provides evidence supporting their claim. International markets may not be as integrated as it was previously believed. In fact, diversification across regions still provides greater risk reduction than diversification across industries. Of course, higher risk reduction will be achieved by diversifying both across regions and across industries, taking into account the volatility transmission patterns found in this study.

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Table 1: FTSE Actuaries classification

BASIC INDUSTRIES	Chemicals Construction & Building Materials Forestry & Paper Steel & Other Metals
CYCLICAL CONSUMER GOODS	Automobiles & Parts Household Goods & Textiles
CYCLICAL SERVICES	General Retailers Leisure & Hotels Media & Entertainment Support Services Transport
FINANCIALS	Banks Insurance Life Assurance Investment Companies Real Estate Speciality & Other Finance
GENERAL INDUSTRIALS	Aerospace & Defence Diversified Industrials Electronic & Electrical Equipment Engineering & Machinery
INFORMATION TECHNOLOGY	Information Tech Hardware Software & Computer Services
NON-CYCLICAL CONSUMER GOODS	Beverages Food Producers & Processors Health Personal Care & Household Products Pharmaceuticals & Biotechnology Tobacco
NON-CYCLICAL SERVICES	Food & Drug Retailers Telecommunication Services
RESOURCES	Mining Oil & Gas
UTILITIES	Electricity Gas Distribution Water

Table 2: Region/Industry effects variances

The table reports the variance of region and industry components for the value-weighted region and industry returns using the Heston and Rouwenhorst (1994) procedure. The full sample period has 2610 daily observations from January 1995 to December 2004. The table also reports the ratio of region to industry effects. The returns are in US dollars and defined in percentages per day.

Region/Industry	Total	Sub-periods		
	1995-2004	1995-1997	1998-2001 TMT crisis	2002-2004
North America	0.0799	0.0229	0.1448	0.0505
European Union	0.4128	0.2409	0.5295	0.4307
Asia	0.9709	0.5051	1.3004	0.9955
Resources	2.3446	0.6692	4.7585	0.8072
Basic Industries	0.2150	0.0554	0.4140	0.1075
General Industrials	0.0918	0.0330	0.1295	0.1008
Cyclical Consumer Goods	0.2411	0.0994	0.4062	0.1632
Non-cyclical Consumer Goods	0.2846	0.0525	0.5197	0.2046
Cyclical Services	0.0731	0.0341	0.1205	0.0493
Non-cyclical Services	0.2649	0.1055	0.4163	0.2237
Utilities	0.3840	0.1235	0.6353	0.3113
Information Technology	0.8230	0.3469	1.2693	0.7050
Financials	0.1246	0.0506	0.2322	0.0555
Region Average	0.4879	0.2563	0.6582	0.4922
Industry Average	0.4847	0.1570	0.8902	0.2728
Region/Industry Ratio	1.0066	1.6322	0.7395	1.8043

Table 3: Results of the linearized asymmetric BEKK model for the Information Technology industry

North America conditional variance equation

$h_{11,t} =$	0.6171	$+0.0358\, h_{11,t-1}$	$+0.0019\, h_{22,t-1}$	$+0.0001\, h_{33,t-1}$	$+0.0169\, h_{12,t-1}$	$+0.0049\, h_{13,t-1}$	$+0.0011\, h_{23,t-1}$	$+0.0281\, \varepsilon^2_{1,t-1}$	$+0.0118\, \varepsilon^2_{2,t-1}$	$+0.0029\, \varepsilon^2_{3,t-1}$ +
	0.0556	0.0066	0.0142	0.0031	0.0600	0.0451	0.0083	0.0213	0.0177	0.0079
	(11.0806)	(5.3890)	(0.1404)	(0.0547)	(0.2820)	(0.1092)	(0.1395)	(1.3183)	(0.6688)	(0.3701)

$-0.0365\, \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	$-0.0181\, \varepsilon_{1,t-1}\varepsilon_{3,t-1}$	$+0.0117\, \varepsilon_{2,t-1}\varepsilon_{3,t-1}$	$+0.1095\, \eta^2_{1,t-1}$	$+0.2532\, \eta^2_{2,t-1}$	$+0.0500\, \eta^2_{3,t-1}$	$+0.3331\, \eta_{1,t-1}\eta_{2,t-1}$	$-0.1481\, \eta_{1,t-1}\eta_{3,t-1}$	$-0.2252\, \eta_{2,t-1}\eta_{3,t-1}$
0.0310	0.0254	0.0156	0.0527	0.0879	0.0440	0.0978	0.0742	0.1064
(-1.1765)	(–0.7127)	(0.7546)	(2.0763)	(2.8794)	(1.1372)	(3.4036)	(–1.9948)	(–2.1154)

European Union conditional variance equation

$h_{22,t} =$	0.1466	$+0.0010\, h_{11,t-1}$	$+0.8134\, h_{22,t-1}$	$+0.0003\, h_{33,t-1}$	$-0.0578\, h_{12,t-1}$	$+0.0012\, h_{13,t-1}$	$-0.0344\, h_{23,t-1}$	$+0.0035\, \varepsilon^2_{1,t-1}$	$+0.0440\, \varepsilon^2_{2,t-1}$	$+0.0009\, \varepsilon^2_{3,t-1}$ +
	0.0664	0.0010	0.0504	0.0010	0.0295	0.0017	0.0478	0.0046	0.0207	0.0027
	(2.2055)	(0.9731)	(16.1359)	(0.3611)	(-1.9609)	(0.6833)	(–0.7196)	(0.7523)	(2.1209)	(0.3566)

$+0.0249\, \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	$+0.0037\, \varepsilon_{1,t-1}\varepsilon_{3,t-1}$	$+0.0131\, \varepsilon_{2,t-1}\varepsilon_{3,t-1}$	$+0.0026\, \eta^2_{1,t-1}$	$+0.1246\, \eta^2_{2,t-1}$	$+0.0090\, \eta^2_{3,t-1}$	$-0.0364\, \eta_{1,t-1}\eta_{2,t-1}$	$+0.0098\, \eta_{1,t-1}\eta_{3,t-1}$	$-0.0672\, \eta_{2,t-1}\eta_{3,t-1}$
0.0158	0.0065	0.0177	0.0059	0.0440	0.0139	0.0410	0.0133	0.0528
(1.5699)	(0.5725)	(0.7426)	(0.4472)	(2.8272)	(0.6534)	(–0.8879)	(0.7381)	(–1.2732)

Asia conditional variance equation									
$h_{33,t} = 0.0746 +$	$0.0006\, h_{11,t-1} +$	$0.0000\, h_{22,t-1} +$	$0.8284\, h_{33,t-1} -$	$0.0000\, h_{12,t-1} +$	$0.0458\, h_{13,t-1} -$	$0.0024\, h_{23,t-1} +$	$0.0127\, \varepsilon^2_{1,t-1} +$	$0.0023\, \varepsilon^2_{2,t-1} +$	$0.0862\, \varepsilon^2_{3,t-1} +$
0.0315	0.0012	0.000	0.0403	0.0011	0.0453	0.0415	0.0070	0.0034	0.0241
(2.3687)	(0.5043)	(0.0291)	(20.5146)	(-0.0578)	(1.0114)	(–0.0583)	(1.8197)	(0.6943)	(3.5763)

$+ 0.0110\, \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	$+ 0.0663\, \varepsilon_{1,t-1}\varepsilon_{3,t-1}$	$+ 0.0286\, \varepsilon_{2,t-1}\varepsilon_{3,t-1}$	$+ 0.0140\, \eta^2_{1,t-1}$	$+ 0.0022\, \eta^2_{2,t-1}$	$+ 0.0081\, \eta^2_{3,t-1}$	$- 0.0113\, \eta_{1,t-1}\eta_{2,t-1}$	$- 0.0214\, \eta_{1,t-1}\eta_{3,t-1}$	$+ 0.0086\, \eta_{2,t-1}\eta_{3,t-1}$
0.0078	0.0211	0.0205	0.0133	0.0055	0.0168	0.0147	0.0243	0.0137
(1.4068)	(3.1330)	(1.3909)	(1.0530)	(0.4133)	(0.4839)	(–0.7695)	(–0.8794)	(0.6286)

Note: h_{11}, h_{22} and h_{33} denote the conditional variance for the North America, European Union and Asia return series, respectively. Below the estimated coefficients are the standard errors, with the corresponding t-values given in brackets.

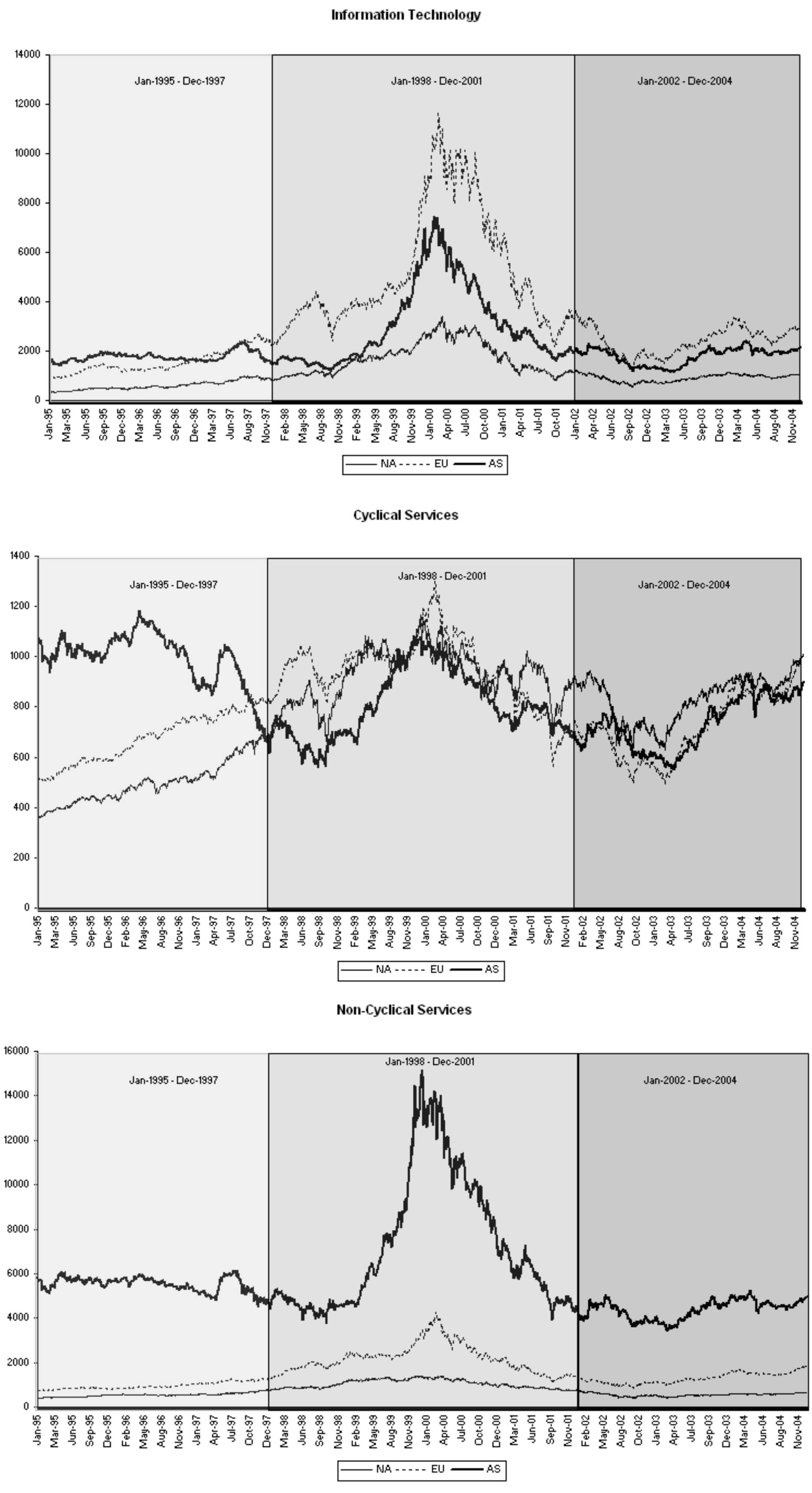

Figure 1: Time series of the Technology, Media and Telecommunications (TMT) related industrial indices

Appendix A. Literature review

Article/s	**Finding**	**Country/Industry**
Lessard (1974), Solnik (1974) and Grinold *et al.* (1989)	Correlation between countries is smaller than correlation between sectors.	Country effects
Heston and Rouwenhorst (1994,1995)	Collected individual stock returns and ran cross-sectional regressions on country and industry dummies in order to quantify the country-specific and the industry-specific components of stock returns. Up to the late 1990s, country effects dominated industry effects.	Country effects
Griffin and Karolyi (1998)	Extended Heston and Rouwenhorst (1994) methodology to stock indices returns and confirmed, regardless of the industry classification, the dominance of country factors.	Country effects
Beckers *et al*. (1992), Drummen and Zimmerman (1992), Beckers *et al*. (1996) and Serra (2000)	Find similar evidence to that found in Griffin and Karolyi (1998).	Country effects
Baca *et al*. (2000)	Study 10 sectors in the 7 largest countries from 1979 to 1999 and find that the impact of the industrial or sector effect is then roughly equal to that of the country effect.	Both equal
Cavaglia *et al*. (2000)	Find similar evidence to that found in Baca *et al*. (2000) by studying 36 industries in 21 developed countries from 1986 to 1999.	Both equal
L' Her *et al*. (2002)	Country effects declined significantly during the nineties and global industry effects surpassed country effects in importance in 1999-2000.	Industry effects
Wang *et al*. (2003)	Use the Heston and Rouwenhorst (1994) methodology and their results indicate that industry effects have significantly dominated country effects in Asian markets since at least 1999.	Industry effects
Flavin (2004)	Examines the Euro zone before and after the introduction of the common currency. They employ the empirical model of Heston and Rouwenhorst (1994), but adopting a panel data approach. They find evidence of a shift in factor importance, from country to industry.	Industry effects
Brooks and Del Negro (2004)	Industry effects have increased since the mid-1990s and have outgrown country effects since 1999. However, excluding the Technology, Media & Telecommunications (TMT) sectors at the heart of the stock market bubble, there is no evidence that industry effects have significantly outgrown country factors in importance.	Country effects
Sell (2005)	Employs an alternative methodology based on cluster analysis techniques. The groups indicate that companies clearly cluster by country rather than by sector and that this effect has become more pronounced over time.	Country effects

Appendix B. Methodology: volatility transmission

The conditional variance for each region can be expanded for the trivariate asymmetric BEKK model as follows:

$$\begin{aligned}
h_{11,t} &= c_{11}^2 + \\
&+ b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + b_{31}^2 h_{33,t-1} + 2b_{11}b_{21}h_{12,t-1} + 2b_{11}b_{31}h_{13,t-1} + 2b_{21}b_{31}h_{23,t-1} + \\
&+ a_{11}^2 \varepsilon_{1,t-1}^2 + a_{21}^2 \varepsilon_{2,t-1}^2 + a_{31}^2 \varepsilon_{3,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \\
&+ g_{11}^2 \eta_{1,t-1}^2 + g_{21}^2 \eta_{2,t-1}^2 + g_{31}^2 \eta_{3,t-1}^2 + 2g_{11}g_{21}\eta_{1,t-1}\eta_{2,t-1} + 2g_{11}g_{31}\eta_{1,t-1}\eta_{3,t-1} + 2g_{21}g_{31}\eta_{2,t-1}\eta_{3,t-1}
\end{aligned} \tag{A1}$$

$$\begin{aligned}
h_{22,t} &= c_{12}^2 + c_{22}^2 + \\
&+ b_{12}^2 h_{11,t-1} + b_{22}^2 h_{22,t-1} + b_{32}^2 h_{33,t-1} + 2b_{12}b_{22}h_{12,t-1} + 2b_{12}b_{32}h_{13,t-1} + 2b_{22}b_{32}h_{23,t-1} + \\
&+ a_{12}^2 \varepsilon_{1,t-1}^2 + a_{22}^2 \varepsilon_{2,t-1}^2 + a_{32}^2 \varepsilon_{3,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{12}a_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{22}a_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \\
&+ g_{12}^2 \eta_{1,t-1}^2 + g_{22}^2 \eta_{2,t-1}^2 + g_{32}^2 \eta_{3,t-1}^2 + 2g_{12}g_{22}\eta_{1,t-1}\eta_{2,t-1} + 2g_{12}g_{32}\eta_{1,t-1}\eta_{3,t-1} + 2g_{22}g_{32}\eta_{2,t-1}\eta_{3,t-1}
\end{aligned} \tag{A2}$$

$$\begin{aligned}
h_{33,t} &= c_{13}^2 + c_{23}^2 + c_{33}^2 + \\
&+ b_{13}^2 h_{11,t-1} + b_{23}^2 h_{22,t-1} + b_{33}^2 h_{33,t-1} + 2b_{13}b_{23}h_{12,t-1} + 2b_{13}b_{33}h_{13,t-1} + 2b_{23}b_{33}h_{23,t-1} + \\
&+ a_{13}^2 \varepsilon_{1,t-1}^2 + a_{23}^2 \varepsilon_{2,t-1}^2 + a_{33}^2 \varepsilon_{3,t-1}^2 + 2a_{13}a_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{13}a_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{23}a_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + \\
&+ g_{13}^2 \eta_{1,t-1}^2 + g_{23}^2 \eta_{2,t-1}^2 + g_{33}^2 \eta_{3,t-1}^2 + 2g_{13}g_{23}\eta_{1,t-1}\eta_{2,t-1} + 2g_{13}g_{33}\eta_{1,t-1}\eta_{3,t-1} + 2g_{23}g_{33}\eta_{2,t-1}\eta_{3,t-1}
\end{aligned} \tag{A3}$$

Equations (A1), (A2) and (A3) reveal how shocks and volatility are transmitted over time and across regions.

Appendix C. Estimation results for the VAR-BEKK model

This table shows the estimation of the model defined in Equations (4) and (5) for the 10 industries considered. It reports estimated parameters for the mean equation and for the variance-covariance matrix, using the full sample period, from January 1995 to December 2004. P-values appear in brackets. In all cases, the necessary conditions for the stationarity of the process are satisfied.

Panel (A). Resources

	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0409 (0.098)	0.0288 (0.210)	-0.0083 (0.715)
$R_{NA,t-1}$	0.0443 (0.043)	0.4218 (0.000)	0.0721 (0.000)
$R_{EU,t-1}$	-0.0240 (0.275)	-0.1421 (0.000)	0.0815 (0.000)
$R_{AS,t-1}$	0.0395 (0.062)	-0.0037 (0.848)	0.0765 (0.000)

$$\hat{C} = \begin{bmatrix} \underset{(0.000)}{0.8405} & \underset{(0.000)}{-0.1323} & \underset{(0.779)}{-0.0214} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0.1079} & \underset{(0.000)}{0.2687} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{-0.0001} \end{bmatrix} \qquad \hat{B} = \begin{bmatrix} \underset{(0.000)}{-0.2494} & \underset{(0.004)}{-0.0469} & \underset{(0.942)}{0.0009} \\ \underset{(0.000)}{-0.4865} & \underset{(0.000)}{-0.9410} & \underset{(0.335)}{-0.0494} \\ \underset{(0.004)}{0.1869} & \underset{(0.000)}{0.1941} & \underset{(0.000)}{0.9301} \end{bmatrix}$$

$$\hat{A} = \begin{bmatrix} \underset{(0.000)}{0.1802} & \underset{(0.006)}{-0.0731} & \underset{(0.001)}{-0.0757} \\ \underset{(0.000)}{-0.1810} & \underset{(0.000)}{0.2360} & \underset{(0.108)}{0.0373} \\ \underset{(0.028)}{0.0771} & \underset{(0.361)}{-0.0136} & \underset{(0.000)}{-0.2166} \end{bmatrix} \qquad \hat{G} = \begin{bmatrix} \underset{(0.000)}{0.4282} & \underset{(0.010)}{0.0741} & \underset{(0.810)}{0.0091} \\ \underset{(0.012)}{-0.1359} & \underset{(0.027)}{0.1019} & \underset{(0.647)}{0.0159} \\ \underset{(0.557)}{0.0324} & \underset{(0.615)}{0.0143} & \underset{(0.000)}{0.2738} \end{bmatrix}$$

Panel (B). Basic Industries			
	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0416 (0.148)	0.0124 (0.575)	-0.0549 (0.144)
$R_{NA,t-1}$	0.1550 (0.000)	0.3021 (0.000)	0.2278 (0.000)
$R_{EU,t-1}$	0.0018 (0.963)	-0.0389 (0.217)	0.0211 (0.692)
$R_{AS,t-1}$	0.0343 (0.150)	-0.0261 (0.155)	0.1096 (0.000)

$$\hat{C}=\begin{bmatrix} \underset{(0.000)}{0.6275} & \underset{(0.000)}{-0.2029} & \underset{(0.000)}{-0.0997} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0.1340} & \underset{(0.000)}{0.0633} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.227)}{0.0355} \end{bmatrix} \qquad \hat{B}=\begin{bmatrix} \underset{(0.000)}{-0.3001} & \underset{(0.000)}{-0.0816} & \underset{(0.000)}{-0.1335} \\ \underset{(0.000)}{-0.4857} & \underset{(0.000)}{-0.8359} & \underset{(0.000)}{0.1694} \\ \underset{(0.004)}{-0.0236} & \underset{(0.000)}{-0.0228} & \underset{(0.000)}{-0.9702} \end{bmatrix}$$

$$\hat{A}=\begin{bmatrix} \underset{(0.000)}{0.2163} & \underset{(0.000)}{0.0928} & \underset{(0.000)}{0.1188} \\ \underset{(0.000)}{0.2771} & \underset{(0.000)}{0.2344} & \underset{(0.092)}{0.0325} \\ \underset{(0.000)}{0.1009} & \underset{(0.000)}{-0.0622} & \underset{(0.000)}{0.0846} \end{bmatrix} \qquad \hat{G}=\begin{bmatrix} \underset{(0.000)}{0.1416} & \underset{(0.000)}{0.0965} & \underset{(0.018)}{-0.0626} \\ \underset{(0.000)}{0.2678} & \underset{(0.000)}{-0.1142} & \underset{(0.000)}{-0.1559} \\ \underset{(0.000)}{-0.1910} & \underset{(0.008)}{0.0302} & \underset{(0.000)}{0.3525} \end{bmatrix}$$

Panel (C). General Industrials			
	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0457 (0.074)	0.0173 (0.400)	-0.0139 (0.542)
$R_{NA,t-1}$	0.0230 (0.282)	0.2710 (0.000)	0.2944 (0.000)
$R_{EU,t-1}$	0.0510 (0.057)	0.0051 (0.812)	0.2072 (0.000)
$R_{AS,t-1}$	-0.0526 (0.014)	-0.0250 (0.149)	-0.0185 (0.332)

$$\hat{C}=\begin{bmatrix} \underset{(0.000)}{0.7447} & \underset{(0.000)}{-0.2932} & \underset{(0.000)}{-0.1926} \\ \underset{(0.000)}{0} & \underset{(0.999)}{-0.0001} & \underset{(0.999)}{-0.0001} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{0.0000} \end{bmatrix} \qquad \hat{B}=\begin{bmatrix} \underset{(0.000)}{0.1911} & \underset{(0.000)}{-0.0775} & \underset{(0.051)}{0.0324} \\ \underset{(0.000)}{0.4534} & \underset{(0.000)}{0.5909} & \underset{(0.000)}{0.0633} \\ \underset{(0.004)}{-0.6332} & \underset{(0.000)}{-0.7547} & \underset{(0.004)}{0.0894} \end{bmatrix}$$

$$\hat{A}=\begin{bmatrix} \underset{(0.000)}{-0.1798} & \underset{(0.001)}{0.0672} & \underset{(0.001)}{0.0894} \\ \underset{(0.000)}{0.3111} & \underset{(0.004)}{-0.1084} & \underset{(0.000)}{0.1451} \\ \underset{(0.045)}{-0.1106} & \underset{(0.000)}{0.1177} & \underset{(0.000)}{0.1052} \end{bmatrix} \qquad \hat{G}=\begin{bmatrix} \underset{(0.000)}{0.3060} & \underset{(0.151)}{0.0507} & \underset{(0.000)}{0.1299} \\ \underset{(0.000)}{0.3107} & \underset{(0.000)}{0.2238} & \underset{(0.316)}{0.0658} \\ \underset{(0.208)}{-0.1166} & \underset{(0.004)}{0.0706} & \underset{(0.000)}{0.1358} \end{bmatrix}$$

Panel (D). Cyclical Consumer Goods			
	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0233 (0.343)	0.0142 (0.526)	0.0040 (0.881)
$R_{NA,t-1}$	-0.0094 (0.659)	0.2596 (0.000)	0.2072 (0.000)
$R_{EU,t-1}$	0.0303 (0.191)	0.0259 (0.220)	0.2113 (0.000)
$R_{AS,t-1}$	-0.0319 (0.071)	-0.0378 (0.019)	-0.0919 (0.000)

$$\hat{C} = \begin{bmatrix} \underset{(0.000)}{0.7764} & \underset{(0.000)}{-0.2420} & \underset{(0.037)}{-0.1244} \\ \underset{(0.000)}{0} & \underset{(0.847)}{-0.0085} & \underset{(0.000)}{0.2014} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{0} \end{bmatrix} \quad \hat{B} = \begin{bmatrix} \underset{(0.000)}{0.1755} & \underset{(0.000)}{-0.0957} & \underset{(0.915)}{-0.0026} \\ \underset{(0.000)}{-0.6526} & \underset{(0.000)}{-0.8767} & \underset{(0.769)}{0.0050} \\ \underset{(0.009)}{-0.0914} & \underset{(0.066)}{0.0182} & \underset{(0.004)}{-0.9419} \end{bmatrix}$$

$$\hat{A} = \begin{bmatrix} \underset{(0.000)}{0.2788} & \underset{(0.030)}{0.0672} & \underset{(0.246)}{-0.0282} \\ \underset{(0.053)}{0.0780} & \underset{(0.000)}{0.2553} & \underset{(0.011)}{0.1056} \\ \underset{(0.030)}{-0.1216} & \underset{(0.180)}{-0.0226} & \underset{(0.000)}{0.2149} \end{bmatrix} \quad \hat{G} = \begin{bmatrix} \underset{(0.859)}{-0.0124} & \underset{(0.000)}{0.1619} & \underset{(0.414)}{-0.0448} \\ \underset{(0.000)}{-0.3771} & \underset{(0.306)}{-0.0753} & \underset{(0.000)}{0.3131} \\ \underset{(0.000)}{-0.1966} & \underset{(0.000)}{-0.1289} & \underset{(0.000)}{-0.1755} \end{bmatrix}$$

Panel (E). Non-cyclical Consumer Goods			
	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0409 (0.051)	0.0262 (0.137)	-0.0036 (0.851)
$R_{NA,t-1}$	0.0299 (0.149)	0.3099 (0.000)	0.1186 (0.000)
$R_{EU,t-1}$	0.0139 (0.553)	-0.0437 (0.028)	0.1539 (0.000)
$R_{AS,t-1}$	-0.0343 (0.102)	-0.0421 (0.017)	-0.0475 (0.014)

$$\hat{C} = \begin{bmatrix} \underset{(0.000)}{-0.6903} & \underset{(0.014)}{0.0657} & \underset{(0.314)}{-0.0345} \\ \underset{(0.000)}{0} & \underset{(0.660)}{-0.0162} & \underset{(0.154)}{0.0611} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{0} \end{bmatrix} \quad \hat{B} = \begin{bmatrix} \underset{(0.000)}{0.2828} & \underset{(0.648)}{0.0097} & \underset{(0.981)}{0.0007} \\ \underset{(0.000)}{0.2846} & \underset{(0.000)}{0.9620} & \underset{(0.083)}{0.0346} \\ \underset{(0.009)}{-0.1260} & \underset{(0.006)}{-0.0271} & \underset{(0.000)}{0.9491} \end{bmatrix}$$

$$\hat{A} = \begin{bmatrix} \underset{(0.108)}{0.1196} & \underset{(0.472)}{-0.0199} & \underset{(0.403)}{0.0256} \\ \underset{(0.000)}{0.4036} & \underset{(0.000)}{0.2230} & \underset{(0.251)}{0.0551} \\ \underset{(0.701)}{0.0286} & \underset{(0.530)}{-0.0234} & \underset{(0.000)}{0.2246} \end{bmatrix} \quad \hat{G} = \begin{bmatrix} \underset{(0.000)}{-0.3763} & \underset{(0.342)}{0.0416} & \underset{(0.752)}{-0.0125} \\ \underset{(0.497)}{0.0732} & \underset{(0.007)}{0.1781} & \underset{(0.000)}{0.3794} \\ \underset{(0.000)}{-0.3041} & \underset{(0.000)}{-0.2004} & \underset{(0.022)}{-0.1312} \end{bmatrix}$$

Panel (F). Cyclical Services			
	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0367 (0.130)	0.0138 (0.416)	-0.0176 (0.421)
$R_{NA,t-1}$	0.0771 (0.000)	0.2597 (0.000)	0.1651 (0.000)
$R_{EU,t-1}$	-0.0179 (0.532)	0.0417 (0.039)	0.1646 (0.000)
$R_{AS,t-1}$	-0.0351 (0.108)	-0.0409 (0.007)	-0.0012 (0.950)

$$\hat{C}=\begin{bmatrix} \underset{(0.000)}{0.7656} & \underset{(0.014)}{-0.2290} & \underset{(0.000)}{-0.1503} \\ \underset{(0.000)}{0} & \underset{(0.144)}{0.0557} & \underset{(0.000)}{-0.1338} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{0} \end{bmatrix} \qquad \hat{B}=\begin{bmatrix} \underset{(0.000)}{0.1581} & \underset{(0.000)}{0.0701} & \underset{(0.766)}{0.0039} \\ \underset{(0.000)}{0.6664} & \underset{(0.000)}{0.8797} & \underset{(0.395)}{0.0115} \\ \underset{(0.130)}{0.0604} & \underset{(0.002)}{-0.0258} & \underset{(0.000)}{0.9299} \end{bmatrix}$$

$$\hat{A}=\begin{bmatrix} \underset{(0.000)}{0.2430} & \underset{(0.005)}{-0.0521} & \underset{(0.398)}{0.0187} \\ \underset{(0.006)}{-0.2046} & \underset{(0.000)}{0.1670} & \underset{(0.000)}{-0.1215} \\ \underset{(0.112)}{0.0698} & \underset{(0.000)}{-0.1084} & \underset{(0.000)}{-0.2284} \end{bmatrix} \qquad \hat{G}=\begin{bmatrix} \underset{(0.000)}{-0.4010} & \underset{(0.000)}{-0.0943} & \underset{(0.007)}{-0.0853} \\ \underset{(0.000)}{-0.4960} & \underset{(0.007)}{-0.1910} & \underset{(0.005)}{0.1501} \\ \underset{(0.000)}{0.1978} & \underset{(0.348)}{0.0198} & \underset{(0.000)}{-0.2502} \end{bmatrix}$$

Panel (G). Non-cyclical Services			
	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0170 (0.500)	0.0285 (0.300)	-0.0180 (0.545)
$R_{NA,t-1}$	-0.0255 (0.224)	0.2311 (0.000)	0.2429 (0.000)
$R_{EU,t-1}$	0.0548 (0.004)	0.0365 (0.080)	0.2316 (0.000)
$R_{AS,t-1}$	0.0010 (0.949)	-0.0710 (0.000)	0.0377 (0.045)

$$\hat{C}=\begin{bmatrix} \underset{(0.000)}{0.9038} & \underset{(0.000)}{-0.1053} & \underset{(0.518)}{-0.0220} \\ \underset{(0.000)}{0} & \underset{(0.000)}{-0.0727} & \underset{(0.000)}{0.1682} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.875)}{0.0158} \end{bmatrix} \qquad \hat{B}=\begin{bmatrix} \underset{(0.000)}{-0.2869} & \underset{(0.000)}{0.0605} & \underset{(0.961)}{0.0010} \\ \underset{(0.000)}{0.5267} & \underset{(0.000)}{0.9306} & \underset{(0.009)}{-0.0238} \\ \underset{(0.000)}{-0.1090} & \underset{(0.000)}{-0.3207} & \underset{(0.000)}{-0.9450} \end{bmatrix}$$

$$\hat{A}=\begin{bmatrix} \underset{(0.000)}{-0.1674} & \underset{(0.002)}{0.0573} & \underset{(0.300)}{-0.0261} \\ \underset{(0.000)}{-0.0778} & \underset{(0.000)}{0.1649} & \underset{(0.089)}{-0.0396} \\ \underset{(0.021)}{0.0591} & \underset{(0.06)}{-0.0222} & \underset{(0.000)}{-0.2306} \end{bmatrix} \qquad \hat{G}=\begin{bmatrix} \underset{(0.000)}{-0.1421} & \underset{(0.000)}{0.1046} & \underset{(0.000)}{0.1073} \\ \underset{(0.000)}{-0.1161} & \underset{(0.000)}{-0.2631} & \underset{(0.004)}{0.1012} \\ \underset{(0.000)}{-0.1449} & \underset{(0.148)}{-0.0264} & \underset{(0.000)}{-0.2832} \end{bmatrix}$$

Panel (H). Utilities

	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0164 (0.400)	0.0328 (0.032)	-0.0051 (0.765)
$R_{NA,t-1}$	0.0667 (0.00)	0.0748 (0.00)	0.0473 (0.006)
$R_{EU,t-1}$	0.0114 (0.653)	0.0496 (0.013)	0.1004 (0.00)
$R_{AS,t-1}$	-0.0519 (0.021)	-0.0470 (0.007)	0.0100 (0.609)

$$\hat{C}=\begin{bmatrix} \underset{(0.063)}{-0.1589} & \underset{(0.000)}{-0.6490} & \underset{(0.498)}{-0.0422} \\ \underset{(0.000)}{0} & \underset{(0.776)}{0.1324} & \underset{(0.088)}{-0.0753} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{0} \end{bmatrix} \qquad \hat{B}=\begin{bmatrix} \underset{(0.039)}{0.0621} & \underset{(0.000)}{0.1890} & \underset{(0.636)}{-0.0047} \\ \underset{(0.000)}{-0.0060} & \underset{(0.539)}{0.0559} & \underset{(0.037)}{-0.0874} \\ \underset{(0.000)}{0.2030} & \underset{(0.000)}{-0.1608} & \underset{(0.000)}{0.9379} \end{bmatrix}$$

$$\hat{A}=\begin{bmatrix} \underset{(0.000)}{0.4341} & \underset{(0.000)}{0.1305} & \underset{(0.808)}{0.0036} \\ \underset{(0.042)}{-0.0762} & \underset{(0.000)}{0.1764} & \underset{(0.945)}{-0.0015} \\ \underset{(0.517)}{-0.0212} & \underset{(0.034)}{-0.0564} & \underset{(0.000)}{0.2462} \end{bmatrix} \qquad \hat{G}=\begin{bmatrix} \underset{(0.000)}{0.2849} & \underset{(0.000)}{-0.2941} & \underset{(0.013)}{0.0580} \\ \underset{(0.000)}{0.3829} & \underset{(0.000)}{0.4746} & \underset{(0.728)}{0.0165} \\ \underset{(0.101)}{-0.0873} & \underset{(0.000)}{-0.1554} & \underset{(0.000)}{-0.2212} \end{bmatrix}$$

Panel (I). Information Technology

	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0436 (0.299)	0.0304 (0.431)	-0.0097 (0.749)
$R_{NA,t-1}$	0.0023 (0.913)	0.4385 (0.000)	0.2767 (0.000)
$R_{EU,t-1}$	0.0294 (0.186)	-0.0693 (0.000)	0.1377 (0.000)
$R_{AS,t-1}$	-0.0206 (0.410)	-0.0955 (0.000)	0.0918 (0.000)

$$\hat{C}=\begin{bmatrix} \underset{(0.000)}{0.7856} & \underset{(0.355)}{0.1265} & \underset{(0.963)}{0.0047} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0.3614} & \underset{(0.769)}{0.0223} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.000)}{-0.2722} \end{bmatrix} \qquad \hat{B}=\begin{bmatrix} \underset{(0.000)}{-0.1894} & \underset{(0.063)}{0.0320} & \underset{(0.294)}{-0.0251} \\ \underset{(0.776)}{-0.0447} & \underset{(0.000)}{-0.9019} & \underset{(0.954)}{0.0013} \\ \underset{(0.910)}{-0.0130} & \underset{(0.471)}{0.0190} & \underset{(0.000)}{-0.9101} \end{bmatrix}$$

$$\hat{A}=\begin{bmatrix} \underset{(0.010)}{0.1678} & \underset{(0.138)}{-0.0593} & \underset{(0.000)}{-0.1129} \\ \underset{(0.147)}{-0.1089} & \underset{(0.000)}{-0.2098} & \underset{(0.144)}{-0.0487} \\ \underset{(0.438)}{-0.0540} & \underset{(0.483)}{-0.0314} & \underset{(0.000)}{-0.2936} \end{bmatrix} \qquad \hat{G}=\begin{bmatrix} \underset{(0.000)}{-0.3310} & \underset{(0.397)}{0.0516} & \underset{(0.037)}{-0.1185} \\ \underset{(0.000)}{-0.5031} & \underset{(0.000)}{-0.3530} & \underset{(0.426)}{0.0478} \\ \underset{(0.023)}{0.2238} & \underset{(0.189)}{0.0953} & \underset{(0.357)}{0.0903} \end{bmatrix}$$

Panel (J). Financials

	$R_{NA,t}$	$R_{EU,t}$	$R_{AS,t}$
μ	0.0515 (0.037)	0.0208 (0.311)	-0.0328 (0.185)
$R_{NA,t-1}$	0.0632 (0.003)	0.2900 (0.000)	0.2500 (0.000)
$R_{EU,t-1}$	0.0077 (0.762)	-0.0017 (0.933)	0.1410 (0.000)
$R_{AS,t-1}$	-0.0278 (0.150)	-0.0295 (0.066)	0.0762 (0.000)

$$\hat{C} = \begin{bmatrix} \underset{(0.000)}{-0.8059} & \underset{(0.000)}{0.1232} & \underset{(0.085)}{0.0931} \\ \underset{(0.000)}{0} & \underset{(0.007)}{-0.1100} & \underset{(0.000)}{-0.1548} \\ \underset{(0.000)}{0} & \underset{(0.000)}{0} & \underset{(0.999)}{0} \end{bmatrix} \quad \hat{B} = \begin{bmatrix} \underset{(0.000)}{0.2035} & \underset{(0.250)}{0.0174} & \underset{(0.023)}{-0.0348} \\ \underset{(0.000)}{0.4295} & \underset{(0.000)}{0.9478} & \underset{(0.137)}{0.1243} \\ \underset{(0.000)}{-0.2059} & \underset{(0.000)}{-0.2500} & \underset{(0.000)}{-0.9601} \end{bmatrix}$$

$$\hat{A} = \begin{bmatrix} \underset{(0.000)}{-0.3881} & \underset{(0.547)}{-0.0118} & \underset{(0.507)}{0.0162} \\ \underset{(0.000)}{0.3503} & \underset{(0.000)}{0.2116} & \underset{(0.082)}{0.0483} \\ \underset{(0.196)}{0.0320} & \underset{(0.501)}{0.0095} & \underset{(0.000)}{0.2243} \end{bmatrix} \quad \hat{G} = \begin{bmatrix} \underset{(0.000)}{-0.3829} & \underset{(0.000)}{-0.0951} & \underset{(0.000)}{-0.1298} \\ \underset{(0.002)}{-0.2007} & \underset{(0.000)}{-0.2123} & \underset{(0.000)}{0.1308} \\ \underset{(0.037)}{-0.1061} & \underset{(0.733)}{0.0064} & \underset{(0.000)}{0.2040} \end{bmatrix}$$

CHAPTER 4

Global vs Regional and Economic vs Financial Integration in European Stock Returns

4.1 Introduction

What is the effect of globalization and further integration on the return and risk structure of international equity markets? The available evidence clearly indicates that correlations tend to increase when countries become increasingly integrated (see e.g. Longin and Solnik (1995), Bekaert and Harvey (2000), Goetzmann *et al*. (2005), Baele (2005), and Baele and Inghelbrecht (2006)). From a theoretical perspective, cross-country equity market correlations can increase either because of a convergence in cross-country cash flows or discount rates. While the former is typically associated with globalization and regional economic integration, the latter is a necessary implication of increasing financial integration.

While there is now considerable agreement that equity market correlations increase with integration, few studies have investigated the relative contribution of respectively economic and financial integration to this increase. Distinguishing between both effects is important for a number of reasons. First, cross-market interdependences and correlations have frequently been used as indirect measures of financial integration. By separately correcting for economic integration, we should obtain a cleaner measure of financial integration. Second, differences in the degree of and time variation in respectively economic and financial integration may explain why equity correlations vary substantially across countries and over time. For instance, is one market more correlated with the world equity market because its cash flows are more similar, because it is relatively better financially integrated, or a combination of both? Last but not least, by identifying the different sources of market comovement in `normal' times, our analysis should also provide for a better identification of the various channels through which contagion may occur.

This chapter analyzes the nature and the changes in the integration of European stock markets from the 1970s to the 2000s. It addresses several related questions. First, how strongly integrated are European stock markets? Second, has this degree of integration intensified over time? Third, should this integration be defined as global integration or regional integration? Finally, is it due to further economic or financial integration? The answer to these questions will obviously have important implications for both portfolio investors and policy markers. Note that there are several possible definitions of the term `integration'. The definition used in this study focuses on the openness of equity markets and directly measures the extent to which shocks are transmitted across equity markets (see Fratzscher (2002) and Baele (2005), among others).

To empirically study the relative importance of global vs. regional and economic vs. financial integration for time-varying market correlations and interlinkages, we focus on 21 European equity markets for a number of reasons. First, over the last years, Europe has gone through an extraordinary period of increasing integration, including the introduction of the euro in 1999 and the accession of 10 new members to the European Union in 2004. Second, the comparison of countries in an economically homogeneous region with those that opted to stay out of the economic (and monetary) union offers an ideal test for the main hypothesis in this chapter. Third, this analysis may hold important lessons for the recently emerged equity markets in Central and Eastern European Countries which have just embarked or are about to embark on the integration process.

Previous papers have reported increasing equity market integration in Europe. Fratzscher (2002) analyzes the integration process of European equity markets since the 1980s. Building on an uncovered interest rate parity condition and a multivariate GARCH model with time-varying coefficients, he concludes that the integration of European equity markets is in large part explained by the drive towards EMU. Similarly, Hardouvelis *et al*. (2006) analyze the degree of integration in the second half of the 1990s. They find that stock markets converged toward full integration, this is, their expected returns became increasingly determined by EU-wide market risk and less by local risk. In a similar attempt to measure European financial integration, Baele *et al*. (2004) present a set of measures to quantify financial integration in the euro area. In particular, they measure integration in five key markets: money, corporate-bond, government-bond, credit, and equity markets. They find different degrees of integration in each of these markets. Similarly, Cappiello *et al*. (2006) assess the degree of financial integration both in the bond and equity markets for a selected number of new EU member states.

In order to analyze empirically market integration in Europe, we use the volatility spillover model of Bekaert and Harvey (1997), Ng (2000), and Baele (2005) as a basic building block. This methodology allows for a decomposition of total local return volatility into a purely country-specific component at the one hand, and a volatility spillover from respectively the global and regional equity markets at the other hand. This decomposition is accomplished by estimating the exposure of local return shocks to unexpected returns on the global and regional equity market indices. Previous studies have typically interpreted an increase in the exposure to common factors as an indicator of integration. Bekaert and Harvey (1997) for instance found that the emerging market returns are increasingly driven by global market shocks after important capital market liberalizations. Similar evidence is reported by Ng (2000) and Baele (2005) for a sample of respectively Pacific-Basin and European countries.

As argued before, the increased exposure to common market shocks can either be the result of a convergence in cash-flow expectations (related to further economic integration) or in discount rates (resulting from increasing financial integration). To distinguish between both, we use the VAR methodology developed in Campbell and Shiller (1988a) and Campbell (1991) to decompose the return on the global market into a component due to revisions in future cash flows and a part due to news about future discount rates. In a recent paper, Campbell and Vuolteenaho (2004) showed that the size and value anomalies in stock returns can be explained by allowing stocks to have a different exposure to cash-flow and discount-rate news. Similarly to Campbell and Mei (1993), in this study, we decompose the exposure or `beta' of local European equity market returns to global market shocks into respectively a cash-flow and discount-rate beta. An increase in economic (financial) integration would be consistent with an increase in the cash-flow (discount-rate) betas.

This chapter is closely related to the work of Ammer and Mei (1996), Phylaktis and Ravazzolo (2002), and Engsted and Tanggaard (2004). Ammer and Mei (1996) decompose the returns on the equity markets of 15 industrialized countries in a cash-flow and discount-rate component over the period 1974-1990. Consequently, they interpret the cross-country correlations between discount and cash-flow news as measures of respectively financial and economic integration. Among other things, they find that real linkages measured using stock market data are much stronger than those that are obtained from pair-wise correlations in industrial production growth rates. Phylaktis and Ravazzolo (2002) perform a similar analysis on a set of Pacific-Basin equity markets. They report increasing economic and financial integration for most countries. Interestingly, they find that economic integration provides an important channel for further financial integration. Engsted and Tanggaard (2004) is similar in spirit to Ammer and Mei (1996). They find that news about future excess returns is the main determinant of stock market volatility in both the US and the UK. This news component is highly cross-country correlated, which helps explain the high degree of comovement between both markets.

This chapter differs from the previous studies in a number of ways. First, we add to the analysis a measure of global and regional integration. Second, as argued before, our focus is entirely on European equity markets. Third, this study looks at exposures to cash-flow and discount-rate shocks as measures of economic and financial integration instead of correlations in respectively cash-flow and discount-rate shocks. The main advantage of looking at exposures rather than at correlations is that the former are not vulnerable to the conditioning bias of Forbes and Rigobon (2002). More specifically, rising cross-country correlations may be purely the result of an increase in the volatility of cash-flow / discount-rate shocks rather than of increasing integration. Finally, our sample period covers a wider range of data including the early 2000s, where the process of further European integration was still taking place.

The remainder of this chapter is organized as follows. Section 2 measures global and regional integration through time. Section 3 describes, first, how global market shocks can be decomposed in news about future cash flows and discount rates and, second, how to measure cash-flow and discount-rate exposures. Section 4 reports the empirical results and some robustness checks. Finally, Section 5 concludes.

4.2 Measuring Global and Regional Integration

Before decomposing global (US) risk into cash-flow and discount-rate risks, we would like to analyze the effects of global (US) and regional (EU) shocks on individual countries. Are European countries more correlated with the US as a global market or with the EU as a relevant regional market? Moreover, we would like to analyze time variation in these correlations. How is global and regional integration evolving through time? If shock exposures have indeed increased, in the following sections we will try to explain why these exposures go up, this is, whether they increase due to economic or financial integration.

Following Ng (2000), Fratzscher (2002) and Baele (2005), we allow for three sources of unexpected returns in individual countries, namely i) a purely domestic shock, ii) a regional European shock, and iii) a global shock proxied through shocks from the US. Moreover, we account for time variation in the spillover parameters by means of dummy variables. In Section 4.2.1 we propose a bivariate spillover model for the US and European returns. Once innovations in these returns are obtained, Section 4.2.2 develops a univariate spillover model for each of the individual European countries where global and regional shocks are introduced as measures of market integration. Finally, Section 4.2.3 presents the main results.

4.2.1 Bivariate spillover model for the US and Europe

The joint process for US and European returns is governed by the following set of equations:

$$r_t = k_0 + Kr_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t \big| \Omega_{t-1} \sim N(0, H_t) \tag{2}$$

where $r_t = [r_{US,t}, r_{EU,t}]'$ represents the monthly returns on, respectively, the US and aggregate European market at time *t*, $\varepsilon_t = [\varepsilon_{US,t}, \varepsilon_{EU,t}]'$ is a vector of innovations, $k_0 = [k_{US,t}, k_{EU,t}]'$, and *K* is a two-by-two matrix of parameters linking lagged returns in the US and Europe to expected returns. The conditional variance-covariance matrix H_t is modeled as an extension of the Constant Conditional Correlation model proposed by Bollerslev (1990). As we expect correlations to change with the degree of integration, this extension allows correlations to vary through time by means of dummy variables. This specification can be represented in the following way:

$$H_t = F_t R_t F_t \tag{3}$$

$$F_t = \begin{bmatrix} h_{US,t} & 0 \\ 0 & h_{EU,t} \end{bmatrix}, \qquad R_t = \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix} \tag{4}$$

where ρ_t is the correlation coefficient and $\rho_t = \rho_0 + \rho_1 D80_t + \rho_2 D90_t + \rho_3 D00_t$. $D80_t$, $D90_t$ and $D00_t$ are dummy variables which take value one in the 1980s, 1990s and 2000s respectively and zero otherwise.

We model the conditional variance $h_{i,t}^2$, where $i = \{US, EU\}$ as a simple asymmetric GARCH(1,1) model (see Glosten *et al*. (1993)):

$$h_{i,t}^2 = \psi_{i,0} + \psi_{i,1}\varepsilon_{i,t-1}^2 + \psi_{i,2}h_{i,t-1}^2 + \psi_{i,3}\varepsilon_{i,t-1}^2 I\{\varepsilon_{i,t-1} < 0\} \tag{5}$$

where I is an indicator function for $\varepsilon_{i,t-1}$ and ψ_i is a vector of parameters. Negative shocks increase volatility if $\psi_{i,3} > 0$.

4.2.2 Univariate spillover models for the European countries

As in Bekaert and Harvey (1997), Ng (2000), Fratzscher (2002) and Baele (2005), local unexpected returns for the 21 European countries considered are allowed to be driven by a purely local component, innovations in European returns and innovations in US returns. Following Baele (2005), as the estimated global and regional shocks estimated in the first step could be driven by common news, we orthogonalize these innovations using a Choleski decomposition. We denote the orthogonalized European and US innovations by $\hat{e}_{EU,t}$ and $\hat{e}_{US,t}$ and their variances by $\sigma_{EU,t}^2$ and $\sigma_{US,t}^2$. We will use these innovations as an input in our second step, where univariate spillover models are estimated for each individual country. In both steps, in order to avoid problems due to non-normality in returns, we use Quasi-Maximum Likelihood estimates (QML) as suggested by Bollerslev and Wooldridge (1992). We do not correct for estimation error in the first step, consequently, this approach yields consistent but not necessarily efficient estimates.

The univariate shock spillover model for each of the 21 European countries is represented by the following set of equations:

$$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

$$\varepsilon_{i,t} = e_{i,t} + \gamma_{i,t}^{EU} \hat{e}_{EU,t} + \gamma_{i,t}^{US} \hat{e}_{US,t} \tag{7}$$

$$e_{i,t} \big| \Omega_{t-1} \sim N(0, \sigma_{i,t}^2) \tag{8}$$

where $e_{i,t}$ is a purely idiosyncratic shock that is assumed to follow a conditional normal distribution with zero mean and variance $\sigma_{i,t}^2$. For simplicity, the expected return $\mu_{i,t-1}$ is a function of lagged US, EU and local returns only. The conditional variance $\sigma_{i,t}^2$ follows an asymmetric GARCH(1,1) process:

$$\sigma_{i,t}^2 = \psi_{i,0} + \psi_{i,1} e_{i,t-1}^2 + \psi_{i,2} \sigma_{i,t-1}^2 + \psi_{i,3} e_{i,t-1}^2 I\{e_{i,t-1} < 0\} \tag{9}$$

Equation (7) allows us to measure the degree of integration of market *i* with the global (US) and regional (EU) markets. Country *i* is more globally (regionally) integrated the stronger domestic returns depend on contemporaneous global (regional) shocks, with $\gamma_{i,t}^{US} (\gamma_{i,t}^{EU})$ as the measure of the degree of integration. Time variation in the spillover parameters $\gamma_{i,t}^{US}$ and $\gamma_{i,t}^{EU}$ is governed by three dummy variables, which allow the US and EU spillover intensities to vary through time following the integration process. Thus, $\gamma_{i,t}^{j} = \gamma_0 + \gamma_1 D80_t + \gamma_2 D90_t + \gamma_3 D00_t$, where $j = \{US, EU\}$.

We decompose total local volatility $h_{i,t}$ into three components: i) a purely local component, ii) a component related to European volatility, and iii) a component related to US volatility. Recall the decomposition of $\varepsilon_{i,t}$ into three components in Equation (7). Assume now that the purely local shocks are uncorrelated across countries, $E[e_{i,t} e_{j,t}] = 0$, for $i \neq j$, and uncorrelated with the European and US benchmark index,

$E[e_{i,t}\hat{e}_{EU,t}]=0$, $E[e_{i,t}\hat{e}_{US,t}]=0$. Moreover, $\hat{e}_{EU,t}$ and $\hat{e}_{US,t}$ are orthogonalized in the first step, implying that

$$E[\varepsilon_{i,t}^2|\Omega_{t-1}]=h_{i,t}=\sigma_{i,t}^2+(\gamma_{i,t}^{EU})^2\sigma_{EU,t}^2+(\gamma_{i,t}^{US})^2\sigma_{US,t}^2 \tag{10}$$

Under these assumptions, the proportion of local variance explained by, respectively, European and US shocks is given by

$$VR_{i,t}^{EU}=\frac{(\gamma_{i,t}^{EU})^2\sigma_{EU,t}^2}{h_{i,t}} \tag{11}$$

$$VR_{i,t}^{US}=\frac{(\gamma_{i,t}^{US})^2\sigma_{US,t}^2}{h_{i,t}} \tag{12}$$

This will also give an idea about time variation in regional (EU) and global (US) integration, though time variation in shock volatilities may also influence the ratios.

4.2.3 Empirical results for spillover models

As explained in the previous sections, we estimate a bivariate GARCH model for the US and European markets and, afterwards, univariate spillover models for the 21 European countries considered[1]. We will focus our analysis on the shock spillover parameters ($\gamma_{i,t}^{EU}$ and $\gamma_{i,t}^{US}$) from Equation (7), and variance proportions ($VR_{i,t}^{EU}$ and $VR_{i,t}^{US}$) from Equations (11) and (12). They are interpreted as measures of regional and global integration.

Our sample contains the 12 EMU countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, and Spain), 3 non-EMU but EU members (Denmark, Sweden and UK), 3 non-EMU but new EU members (Czech Republic, Hungary and Poland), 1 EU candidate country (Turkey) and 2 other European countries (Norway and Switzerland). In total, we analyze 21 European countries. We will study whether there are differences in integration between the

[1] Detailed estimation results for the bivariate and univariate spillover models are available upon request.

groupings considered. We obtain monthly returns from Datastream over the period 1973-2005. There is a somewhat shorter time period for a few countries where time series started later. Returns are denominated in US$ to match the currency of the cash-flow and discount-rate news variables. Finally, the EU index used for the empirical estimation of univariate spillover models for each country excludes this country from the index in order to focus only on shocks that are external to each market.

Table 1 reports EU and US shock spillover intensities ($\gamma_{i,t}^{EU}$ and $\gamma_{i,t}^{US}$) over the different subperiods considered. This will enable us to understand the magnitude and evolution of shock spillover intensity through time, as well as the differences among the countries considered. In all countries, except Finland, Ireland, UK and Turkey, the sensitivity to EU shocks is considerably larger in the 2000s than in the first decade of data available. On average, the EU spillover intensity increased from about 0.70 in the second half of the 1970s to about 1.04 in the first half of the 2000s. The largest increases were observed in two new EU members, Poland and the Czech Republic, with an increase of around 100% and 67% respectively from the 1990s to the 2000s. They are followed by two EMU members, Germany and Austria, with an increase of, respectively, 61% and 60% from the 1970s to the 2000s.

The rise in US shock spillover intensity is also very pronounced. In all countries, except Greece, Portugal, UK, Hungary, Poland and Norway, the sensitivity to US shocks is considerably larger in the 2000s than in the first decade of data available. On average, the US spillover intensity increased from about 0.48 in the second half of the 1970s to about 0.84 in the first half of the 2000s. The increase is strongly above the average in Turkey (415%), Luxembourg (114%) and Germany (64%).

The countries with higher spillover intensities from the EU are Greece, Poland, the Czech Republic and Belgium, being the less affected by EU shocks the UK. Interestingly, among the first ones there are two EMU members and two new EU members. The countries with higher spillover intensities from the US are Turkey, Sweden and Finland, being Austria the less affected by US shocks. This time, the first countries are non-EMU countries, which implies a lower degree of integration with the EU, as compared to other countries.

Table 2 reports the proportion of total return variance that can be attributed to EU and US shock spillovers ($VR_{i,t}^{EU}$ and $VR_{i,t}^{US}$). If we recall from the CAPM that expected local returns in a fully integrated market depend only on non-diversifiable international factors then, intuitively, the higher the proportion of variance explained by US and EU shocks, the higher the integration of local markets. If we look at the evolution of these proportions in time, all countries are in the 2000s more integrated than in the 1970s. If we add up the proportions of variance explained by US and EU shocks, the three countries with a higher proportion of variance explained by international factors are France, The Netherlands and Germany. On the other hand, among the 21 countries considered, the less integrated markets would be those of Austria, the Czech Republic and Turkey. Both the US and European markets have gained considerably in importance for individual European financial markets, though Europe has not taken over from the US as the dominant market in Europe (as suggested by Fratzscher (2002)). This would just be the case for new EU members where, in the 2000s, the proportion of variance explained by EU shocks is larger than the one explained by US shocks.

In general, among the 12 EMU members, the proportion of variance explained by EU shocks is larger in the 2000s than in the first decade of data available. The exceptions are Finland, Ireland, Luxembourg and The Netherlands, small countries where this proportion of variance has decreased. The same occurs with the proportion of variance explained by US shocks, which has increased except for Austria and Portugal. For EU but non-EMU members (Denmark, Sweden and UK) the proportion of variance explained by EU shocks has decreased while the one explained by US shocks has increased in time. For new EU members, EU shocks have gained importance in all countries, whereas the proportion of variance explained by US shocks has increased (Czech Republic), decreased (Poland) or remained the same (Hungary) depending on the country. In the last period, the highest EU variance ratios were observed in Hungary (50%), Portugal (44%) and Belgium (43%); the lowest in Turkey (2%), Finland (5%) and Denmark (9%). As expected, Germany (63%), France (62%), The Netherlands (61%) and UK (61%) have high US variance ratios, while especially Austria (4%) and the Czech Republic (6%) are relatively isolated from the US market. In general, the new EU members still have very low proportions of variance explained by US shocks.

4.3 Decomposing Global Risk into Cash-flow and Discount-rate Risk

Once global and regional integration are measured, it is even more interesting to investigate the relative contribution of respectively economic (cash flows) and financial (discount rates) integration in each of these factors. Both the US and European markets have gained considerably in importance for individual European financial markets, though the US is still the dominant market for most European countries. This increase in integration is due to economic or financial integration? In the remainder of this chapter, we will show how to decompose global (US) risk into cash-flow and discount-rate risk. A similar decomposition could be obtained for regional market betas, i.e. the cash-flow and discount-rate betas with respect to the aggregate European market[2].

4.3.1 Cash-flow and discount-rate risk

As in Campbell and Shiller (1988a) and Campbell (1991), we use the log-linear approximate decomposition of returns:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \tag{13}$$

$$r_{t+1} - E_t r_{t+1} = N_{CF,t+1} - N_{DR,t+1} \tag{14}$$

where r_{t+1} is a log stock return, d_{t+1} is the log dividend yield, Δ denotes a one-period change, E_t denotes a rational expectation at time *t*, and ρ is a discount-rate coefficient. $N_{CF,t+1}$ denotes news about future cash flows at time *t+1*. Similarly, $N_{DR,t+1}$ represents news about future discount rates. Notice that Equation (13) can be considered as a consistent model of expectations, since a positive (negative) unexpected return today must be only associated with an upward (downward) revision in

[2] Such an extension is not straightforward, given that we need to provide for a model of cash-flow and discount-rate news in an environment of time-varying capital market integration. This greatly complicates the modeling of expected returns and dividends: While under full integration only global / regional information variables are relevant, only local instruments are to be used in case of full market segmentation. We leave this analysis for further research.

expectations about future cash flows, a downward (upward) revision in expectations about future returns, or a combination of both.

To implement this decomposition, we follow Campbell (1991) and estimate the cash-flow news and discount-rate news series using a vector autoregressive (VAR) model. This VAR methodology first estimates the terms $E_t r_{t+1}$ and $(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ and then uses r_{t+1} and Equation (13) to back out the cash-flow news. This practice has an important advantage - one does not necessarily have to understand the short-run dynamics of dividends. Understanding the dynamics of expected returns is enough.

We assume that the data are generated by a first-order VAR model

$$z_{t+1} = a + \Gamma z_t + u_{t+1} \tag{15}$$

where z_{t+1} is a m-by-1 state vector with r_{t+1} as its first element, a and Γ are an *m*-by-*1* vector and *m*-by-*m* matrix of constant parameters, and u_{t+1} an i.i.d. *m*-by-*1* vector of shocks. Of course, this formulation also allows for higher-order VAR models via a simple redefinition of the state vector to include lagged values.

Provided that the process in Equation (15) generates the data, *t+1* cash-flow and discount-rate news are linear functions of the *t+1* shock vector:

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1} \tag{16}$$

$$N_{DR,t+1} = e1'\lambda u_{t+1} \tag{17}$$

The VAR shocks are mapped to news by λ, defined as $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$. The long-run significance of each individual VAR shock to discount-rate expectations is captured by $e1'\lambda$, where *e1* is a vector whose first element is equal to one and zero otherwise. The greater the absolute value of a variable's coefficient in the return prediction equation (the top row of Γ), the greater the weight the variable receives in the discount-rate-news formula. More persistent variables should also receive more weight, which is captured by the term $(I - \rho\Gamma)^{-1}$.

4.3.2 Measuring global cash-flow and discount-rate exposures

We showed in the previous section how returns can be decomposed into two components. An interesting question is whether increasing exposure to global shocks is a result of increasing exposure to cash-flow news or increasing exposure to discount-rate news. Moreover, different countries may have different betas or exposures to these two components of the global market. Following Campbell and Vuolteenaho (2004), we define the cash-flow beta as

$$\beta_{i,CF} \equiv \frac{Cov(r_{i,t}^{e}, N_{CF,t})}{Var(r_{US,t}^{e} - E_t r_{US,t}^{e})} \tag{18}$$

and the discount-rate beta as

$$\beta_{i,DR} \equiv \frac{Cov(r_{i,t}^{e}, -N_{DR,t})}{Var(r_{US,t}^{e} - E_t r_{US,t}^{e})} \tag{19}$$

Therefore, the global market beta can be decomposed into components in a simple way:

$$\beta_{i,US} = \beta_{i,CF} + \beta_{i,DR} = \gamma_i^{US} \tag{20}$$

We define betas by using unconditional variances and covariances. However, we will report betas using the whole sample period and also betas using the same subperiods as before, in order to get an idea of their evolution in time. An increase in economic and financial integration would be consistent with an increase in respectively $\beta_{i,CF}$ and $\beta_{i,DR}$. This framework enables us to analyze the variation across countries and across time in the two components of the market beta.

4.4 Empirical Results

In this section, we first discuss the decomposition of global (US) equity market shocks into cash-flow and discount-rate news. Second, we decompose the exposures of 21 European equity markets to US equity market shocks into a cash-flow and discount-rate beta. Finally, we present some robustness checks.

4.4.1 US cash-flow and discount-rate news

Section 4.3 explained how unexpected stock returns can be decomposed into a component due to revisions in future cash flows and a part due to revisions in future discount rates within a straightforward first-order VAR framework. To operationalize this VAR approach, we need to specify the variables to be included into the state vector ($\mathbf{z}_{t+1}$). Following Campbell and Vuolteenaho (2004), we choose the following four state variables: the excess market return (measured as the log excess return on the CRSP value-weighted index over Treasury bills), the yield spread between long-term and short-term bonds (measured as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes, in annualized percentage points), the market's smoothed price-earnings ratio (measured as the log ratio of the S&P500 price index to a ten-year moving average of S&P500 earnings), and the small-stock value spread (measured as the difference between the log book-to-market ratios of small value and small growth stocks). Our monthly data covers the period January 1929 - December 2005. For January 1929 - December 2001, data is taken from Tuomo Vuolteenaho's website. For the rest of the sample period, we obtain the variables following Campbell and Vuolteenaho (2004). Thus, excess market return data is from CRSP, yield spread data is from FRED (Federal Reserve Economic Data), the price-earnings ratio is from Shiller (2000), and the small-stock value spread is constructed from the data made available by Professor Kenneth French on his web site[3]. Summary statistics are reported in Table 3.

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The first two predictor variables have become standard instruments in the return predictability literature. The term spread variable is consistently shown to be a leading indicator of real economic activity, and hence stock prices. Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) show that for the United States the yield spread significantly outperforms other financial and macroeconomic indicators in forecasting recessions. Bernard and Gerlach (1998), Estrella and Mishkin (1997), and Ahrens (2002) present similar results for other countries. In addition, several papers (Campbell (1987); Fama and French (1989); Campbell and Yogo (2006), for example) have found a positive relation between the term structure and equity returns. Second, high price-earnings ratios are associated with low long-run expected returns, at least to the extent that earnings growth is constant. For instance, Fama and French (1988) and Campbell and Shiller (1988b) find that price-dividend and price-earnings ratios predict future real equity returns, and, more recently, Campbell and Vuolteenaho (2004) and Hecht and Vuolteenaho (2006) also provide evidence on how log price-earnings ratios negatively predict returns. The third, less standard, variable is the small-stock value spread. Campbell and Vuolteenaho (2004) offer a number of reasons for why this variable may be linked to expected returns. First, small growth stocks may generate cash flows in the more distant future and therefore their prices are more sensitive to changes in discount rates. Second, small growth companies may be particularly dependent on external financing and thus are sensitive to equity market and broader financial conditions. Finally, they argue that episodes of irrational investor optimism are likely to have a particularly powerful effect on small growth shocks.

Table 4 reports the parameter estimates for the VAR model. Row 1 to 4 correspond to respectively the equations for the excess equity market returns, the term spread, the price-earnings ratio, and the small-stock value spread. The first five columns report coefficients on the five explanatory variables: a constant, and lags of the excess market return, term yield spread, price-earnings ratio, and small-stock value spread. OLS standard errors and Bootstrap standard errors are also reported. The final two columns report the R^2 and F statistics for each regression. The first row of Table 4 shows that all predictor variables have a statistically significant relation with the excess market returns. The coefficient on the lagged market return amounts to 0.0949, consistent with a modest degree of momentum. The term yield spread positively predicts the market return. The term spread accounts for a term or maturity risk premium, therefore leading to that positive relation (see Fama and French (1989)). The smoothed price-earnings ratio is - consistent with previous findings - negatively related to expected returns. Finally, the small-stock value spread negatively predicts stock returns, consistent with findings in Eleswarapu and Reinganum (2004) and Brennan *et al*. (2004). The R^2 is reasonable for a monthly expected return model. Rows 2 till 4 summarize the dynamics of the explanatory variables. The term spread has a high degree of autocorrelation (AR(1) coefficient of 0.9138). Interestingly, also the small-stock value spread has some predictive power for the term spread. Finally, the price-earnings ratio and the small-stock value spread ratio are both highly persistent, with roots (very) close to unity.

Table 5 reports summary statistics of the cash-flow and discount-rate news variables as implied by the VAR estimates. A first observation is that discount-rate news is double as volatile as cash-flow news (a monthly volatility of respectively 4.84% and 2.62%). This confirms the finding of Campbell (1991) that discount-rate news is the dominant component of the market return. The table also shows that the two components of return are almost uncorrelated with one another. Following Campbell and Vuolteenaho (2004), Table 5 also reports the correlations of each state variable innovation with the estimated news terms, and the coefficients $(e1' + e1'\lambda)$ and $e1'\lambda$ that map innovations to cash-flow and discount-rate news. Innovations to returns are highly negatively correlated with discount-rate news, reflecting the mean reversion in stock prices that is implied by our VAR system. Market-return innovations are weakly positively correlated with cash-flow news, indicating that some part of a market rise is typically justified by underlying improvements in expected future cash flows. Innovations to the price-earnings ratio, however, are weakly negatively correlated with cash-flow news, suggesting that price increases relative to earnings are not usually justified by improvements in future earnings growth.

4.4.2 Cash-flow and discount-rate betas

In this section, we investigate whether the 21 local European equity returns considered have become more exposed to US equity market shocks, and to what extent this increased exposure is due to a convergence in cash-flow and/or discount-rate news.

Table 6 reports estimates of the total, cash-flow and discount-rate beta with respect to the US market for all countries over the full period and the subperiods 1973-1979, 1980-1989, 1990-1999, and 2000-2005. Figure 1 plots the average total, cash-flow and discount-rate betas over the four subperiods, while Figure 2 compares the cash-flow and discount-rate betas across countries. Consistent with Baele (2005) and Baele and Inghelbrecht (2006), we find a substantial increase in the exposure of local European equity markets to US equity market shocks. More specifically, the average US market exposure increased from about 0.48 in the second half of the 1970s to 0.61 in the 1980s, 0.68 in the 1990s, and 0.88 in the period 2000-2005. Panel B and C of Table 6 and Figure 2 clearly show that this increase is nearly entirely the result of an increase in discount-rate betas. Cash-flow betas are generally very small, statistically insignificant, and if anything, decreasing over time. We conclude from this analysis that the increased exposure of local European equity markets to the US market is largely the result of increased European financial market integration. This analysis also shows that global (regional) market exposures are a useful measure of financial market integration in a sense that the effect of further economic integration on market betas is only of second order.

4.4.3 Robustness checks

In this section, we present a number of additional exercises we have performed in order to examine the robustness of our results in the decomposition of global shocks into cash-flow and discount-rate factors.

4.4.3.1 Post-1952 data

According to Chen and Zhao (2006), an interesting robustness check is to estimate cash-flow and discount-rate news using only postwar data. They suggest it is worth analyzing this because Campbell (1991) documents a shift in variance from cash-flow news to discount-rate news after 1952 and CAPM breaks down only in the postwar period. In Table 7, model 2, we report the results for the benchmark case when only postwar data is used. In this case, discount-rate news continues to be more important than cash-flow news, though, surprisingly, there is now less difference between both. Discount-rate betas continue to be more important than cash-flow betas and their evolution in time is similar to the benchmark case. The only exception is the average of the 12 EMU members. In this case, there seems to be an increasing trend (instead of decreasing trend) in cash-flow betas from the 1970s to the 2000s.

4.4.3.2 Sensitivity to changes in VAR state variables

Following Campbell and Vuolteenaho (2004), our benchmark VAR model includes the excess market return, the term spread, the market's smoothed price-earnings ratio, and the small-stock value spread. However, there are other variables that are often used to predict stock returns. In Table 7 we report some of the results obtained in this study when we include other variables in the VAR system. We report the variance of cash-flow news and discount-rate news, their covariance, cash-flow betas, discount-rate betas, and their evolution in time. We report average betas for: i) the 12 EMU members, ii) the 3 non-EMU but EU members and, iii) 3 non-EMU and new EU members.

In the first column, model 1, where the benchmark case is used, the cash-flow variance is 0.07% and the discount-rate variance is 0.23%. Therefore, consistent with Campbell and Ammer (1993) and Campbell and Vuolteenaho (2004), discount-rate news far exceeds cash-flow news in driving US equity returns. In model 3, following Chen and Zhao (2006), we replace the price-earnings ratio from the benchmark case by a similar variable that also works as a proxy for expected returns[4], the dividend yield. We find that the cash-flow variance is 0.16% and the discount-rate variance is 0.10%. This is, the trend is reversed. In model 4, we use the average value spread instead of the small-stock value spread. The results are very similar to those reported for the benchmark model. Following Liu and Zhang (2006), in models 5 and 6, we use the book-to-market spread and market-to-book spread instead of the value spread as useful predictors of returns. The results are also similar to the benchmark case. In model 7, we follow Campbell and Vuolteenaho (2004) and add to the benchmark case two variables that are often used to predict stock returns: the dividend yield and the Treasury bill rate.

[4] See Campbell and Shiller (1988a), Campbell and Ammer (1993), Campbell and Mei (1993) and Campbell and Vuolteenaho (2004).

With this combination of variables, results are also very similar to those reported for the benchmark case. Finally, model 8 includes the set of variables from Petkova (2006): the excess market return, the term spread, the dividend yield, the default spread (Baa yield over Aaa yield), and the Treasury bill rate. As it happened in model 3, replacing the price-earnings ratio by the dividend yield, will make the cash-flow news more important.

If we focus on betas and we exclude models 3 and 8 from our analysis, all models seem to point out that discount-rate betas are higher than cash-flow betas. This result is also robust across countries. Moreover, both betas are higher for less EU-integrated countries. For instance, the 3 new EU members have always higher betas than the 12 EMU members. If we focus on the evolution of betas in time, discount-rate betas have increased both in the 12 EMU members and in the 3 non-EMU but EU members. However, they have decreased in the 3 new EU member states. These results are robust across models. Regarding cash-flow betas, there is a general decreasing trend across models if we look at the 3 non-EMU but EU members and the 3 new EU members, but there is not homogeneity in results across models if we look at the 12 EMU members (some models account for a decrease in cash-flow betas and some of them for an increase in betas).

The results are robust to adding many other known return predictors to the VAR system as long as the price-earnings ratio is included in the system. Therefore, it should be noted that our results depend critically on the inclusion of the price-earnings ratio in our aggregate VAR system. If we exclude the price-earnings ratio from the system (models 3 and 8) we no longer find that discount-rate betas are higher than cash-flow betas. As Campbell and Vuolteenaho (2004) and Chen and Zhao (2006) point out, the importance of any state variable depends on the coefficient in the VAR estimation and its persistence. In our benchmark case, the price-earnings ratio is the dominant factor due to its persistence. Campbell and Vuolteenaho (2004) contains a detailed discussion of various reasons why this variable should predict stock returns and should, therefore, be included in the VAR. In fact, the benchmark case gives the best predictive power (adjusted R^2 at 2.10%), if we compare it with those of models 3 (adjusted R^2 at 1.67%) and 8 (adjusted R^2 at 1.14%).

Finally, the results are also robust to estimating the VAR using real (instead of excess) market returns.

4.4.3.3 Directly modeling cash-flow news

The return decomposition framework treats cash-flow news as a residual component of the stock return. As pointed out by Campbell and Mei (1993), if Equation (13) is an accurate approximation, and if the VAR system fully describes the true process for expected returns, then this residual calculation procedure should accurately measure cash-flow news. However, if the VAR process used is misspecified, then the residual cash-flow news measure may be a poor proxy for actual cash-flow news. This is one of the reasons why we rely on the results obtained with our benchmark VAR model. It gives the best predictive power among the models analyzed in the robustness check. According to Campbell and Ammer (1993), if one finds that most of the variability of unexpected returns is due to the component obtained as a residual, then its large estimated magnitude may be spurious simply as the result of insufficient predictability in the VAR system. In our benchmark case, even though the cash-flow news is obtained as a residual, most of the variability is due to discount-rate news, which gives robustness to our results. Nevertheless, following Campbell and Mei (1993) and Chen and Zhao (2006), among others, we directly model cash-flow news in order to obtain a further robustness check for our results.

We adopt a separate VAR system for the dividend growth rate and we revise our earlier log-linear approximation as follows:

$$r_{t+1} - E_t r_{t+1} = N^{*}_{CF,t+1} - N_{DR,t+1} + residual \tag{21}$$

where $N_{DR,t+1}$ is the same as before. The residual variable is the component of unexpected returns not captured by our modeled cash-flow news and discount-rate news.

If we propose now a first-order VAR model where z^*_{t+1} is a state vector with the dividend growth rate as its first element and excess market return and dividend yield as the other components, it can be easily shown that:

$$N^*_{CF,t+1} = e1'\lambda^* u^*_{t+1} \tag{22}$$

where $\lambda^* = (I - \rho\Gamma^*)^{-1}$, Γ^* is the companion matrix, and u^*_{t+1} is the residual vector from this new VAR. Finally, we obtain the residual component after $N_{DR,t+1}$ and $N^*_{CF,t+1}$ are both considered.

In Table 8 we report cash-flow ($\beta^*_{i,CF}$) and discount-rate betas ($\beta_{i,DR}$) when both components are directly modeled. In addition, we present the residual beta and the cash-flow beta plus the residual beta, which is equivalent to the cash-flow beta ($\beta_{i,CF}$) if we model only the discount-rate news but back out the cash-flow news as the residual. As seen, the results for this new decomposition system still indicate that, in all countries analyzed, discount-rate news account for most of the variation in stock returns. These results confirm and strengthen the results from Table 6.

4.5 Conclusion

This chapter analyzes global vs. regional and economic vs. financial integration in European equity markets. In order to measure global and regional integration we look at shock spillover intensities and proportions of variance explained by US and EU shocks for 21 local European countries. In general, shock spillover intensity has increased in time, suggesting a higher degree of both regional and global integration. The countries with higher spillover intensities from the EU are two EMU members (Greece and Belgium) and two new EU members (Poland and the Czech Republic), while the countries with higher spillover intensities from the US are non-EMU members (Turkey and Sweden). If we add up the proportions of variance explained by US and EU shocks, the three countries with a higher proportion of variance explained by international factors are France, The Netherlands and Germany, whereas Austria, the Czech Republic and Turkey are the less internationally integrated countries. In general, both the US and European markets have gained considerably in importance for individual European financial markets, though Europe has not taken over from the US as the dominant market in Europe. This would just be the case for new EU members, where the proportion of variance explained by EU shocks is larger than the one explained by US shocks.

But the main goal of this chapter is to investigate to what extent the increased exposure of 21 local European equity markets with respect to US market shocks is the result of a convergence in cash flows or a convergence in discount rates. The former would be consistent with globalization and further economic integration, the latter with further financial integration. In a first step, we decompose monthly US equity market returns into a component due to revisions in future cash flows (cash-flow news) and due to revisions in future discount rates (discount-rate news) using the VAR framework of Campbell (1991). Second, we confirm that betas of local European equity markets with respect to the US market have increased substantially over time. We find that this increase is nearly fully the consequence of an increase in the discount-rate beta. We see this as evidence that the increased correlation of European equity markets with global equity markets is the result of improved financial integration, and to a much lesser extent economic integration.

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Table 1: Shock spillover intensity over time

This table reports shock spillover intensities ($\gamma_{i,t}^{EU}$ and $\gamma_{i,t}^{US}$) from the EU and the US equity markets to the different local European equity markets considered based upon the univariate spillover model in Equations (6-8). Local European equity markets are grouped into the following categories: i) EMU countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Portugal, Spain and The Netherlands), ii) non-EMU but EU countries (Denmark, Sweden and UK), iii) new EU countries (Czech Republic, Hungary and Poland), iv) EU candidates (Turkey) and v) other European countries (Norway and Switzerland). We report results for the different subperiods considered.

	Shock spillover intensity from							
	EU				US			
	70s	80s	90s	00s	70s	80s	90s	00s
Austria	0.37	0.64	1.10	0.94	0.20	0.09	0.46	0.23
Belgium	0.70	0.88	0.74	1.28	0.53	0.52	0.60	0.60
Finland			0.81	0.71			0.96	1.19
France	0.80	1.04	0.94	1.12	0.67	0.61	0.69	0.96
Germany	0.45	0.68	0.93	1.14	0.28	0.44	0.71	1.16
Greece			0.96	1.45			0.76	0.75
Ireland	1.32	0.75	0.80	0.71	0.50	0.66	0.82	0.87
Italy	0.74	0.90	1.01	1.25	0.27	0.29	0.69	0.76
Luxembourg			0.94	1.07			0.42	0.89
Portugal			1.04	1.22			0.62	0.50
Spain		0.58	1.00	1.00		0.53	0.88	0.81
Netherlands	0.60	0.70	0.76	1.02	0.54	0.62	0.67	0.94
Denmark	0.41	0.51	0.94	0.59	0.29	0.49	0.47	0.77
Sweden		0.73	1.13	1.11		0.52	0.86	1.31
UK	1.07	0.58	0.58	0.53	0.98	0.75	0.63	0.72
Czech Rep			0.77	1.28			0.34	0.37
Hungary			1.02	1.25			0.66	0.51
Poland			0.68	1.35			1.29	0.81
Turkey			1.81	0.80			0.40	2.04
Norway		0.80	0.95	1.12		0.81	0.89	0.78
Switzerland	0.58	0.76	0.79	0.84	0.52	0.51	0.68	0.60

Table 2: Variance proportions over time

This table reports what proportion of the variance of unexpected returns in the different local European markets is explained by EU and US shocks ($VR_{i,t}^{EU}$ and $VR_{i,t}^{US}$). These are calculated using estimates from the univariate spillover model in Equations (6-8). Local European equity markets are grouped into the following categories: i) EMU countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Portugal, Spain and The Netherlands), ii) non-EMU but EU countries (Denmark, Sweden and UK), iii) new EU countries (Czech Republic, Hungary and Poland), iv) EU candidates (Turkey) and v) other European countries (Norway and Switzerland). We report results for the different subperiods considered.

	Proportion of variance explained by							
	EU shocks				US shocks			
	70s	80s	90s	00s	70s	80s	90s	00s
Austria	0.15	0.26	0.36	0.29	0.04	0.01	0.11	0.04
Belgium	0.35	0.35	0.26	0.43	0.19	0.13	0.32	0.25
Finland			0.10	0.05			0.25	0.36
France	0.24	0.35	0.33	0.31	0.17	0.13	0.33	0.62
Germany	0.19	0.27	0.31	0.23	0.06	0.11	0.32	0.63
Greece			0.14	0.28			0.16	0.20
Ireland	0.48	0.21	0.21	0.13	0.07	0.18	0.41	0.49
Italy	0.18	0.22	0.20	0.36	0.03	0.02	0.16	0.36
Luxembourg			0.33	0.22			0.13	0.40
Portugal			0.32	0.4			0.21	0.20
Spain		0.25	0.26	0.28		0.24	0.37	0.47
Netherlands	0.34	0.38	0.33	0.27	0.27	0.31	0.45	0.61
Denmark	0.12	0.15	0.35	0.09	0.06	0.14	0.16	0.43
Sweden		0.23	0.26	0.17		0.14	0.28	0.61
UK	0.24	0.18	0.21	0.17	0.23	0.3	0.37	0.61
Czech Rep			0.08	0.28			0.03	0.06
Hungary			0.27	0.50			0.22	0.22
Poland			0.03	0.21			0.25	0.20
Turkey			0.12	0.02			0.01	0.36
Norway		0.18	0.19	0.28		0.20	0.29	0.35
Switzerland	0.30	0.39	0.25	0.28	0.23	0.18	0.33	0.36

Table 3: Descriptive statistics of the VAR state variables

The table shows the descriptive statistics of the VAR state variables estimated from the full sample period 1928:12-2005:12, 925 monthly data points. $R^e_{M,t}$ is the excess log return on the CRSP value-weight index. TY_t is the term yield spread in percentage points, measured as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes. PE_t is the log ratio of S&P500's price to S&P500's ten-year moving average of earnings. VS_t is the small-stock value spread, the difference in the log book-to-market ratios of small value and small growth stocks. "Stdev." denotes standard deviation and "Autocorr." the first-order autocorrelation of the series.

Variable	Mean	Median	Stdev.	Min	Max	Autocorr.
$R^e_{M,t}$	0.0043	0.0093	0.0548	-0.3442	0.3222	0.1022
TY_t	0.7059	0.5700	0.7373	-1.3500	3.1400	0.9268
PE_t	2.8878	2.8868	0.3742	1.5006	3.8906	0.9914
VS_t	1.6511	1.5250	0.3668	1.1922	2.7134	0.9909
Correlations	$R^e_{M,t}$	TY_t	PE_t	VS_t		
$R^e_{M,t}$	1					
TY_t	0.0580	1				
PE_t	-0.0064	-0.1134	1			
VS_t	-0.0314	-0.3679	-0.3154	1		

Table 4: VAR parameter estimates

The table shows the OLS parameter estimates for a first-order VAR model including a constant, the log excess market return ($R^e_{M,t}$), term yield spread (TY_t), price-earnings ratio (PE_t), and small-stock value spread (VS_t). Each set of three rows corresponds to a different dependent variable. The first five columns report coefficients on the five explanatory variables, and the remaining columns show R^2 and F statistics. OLS standard errors are in square brackets and bootstrap standard errors are in parentheses. Bootstrap standard errors are computed from 2500 simulated realizations. Sample period for the dependent variables is 1928:12-2005:12, 925 monthly data points.

	Constant	$R^e_{M,t}$	TY_t	PE_t	VS_t	R^2 %	F
$R^e_{M,t+1}$	0.0656	0.0949	0.0051	-0.0156	-0.0122	2.52	5.95
	[0.0191]	*[0.0326]*	*[0.0026]*	*[0.0050]*	*[0.0054]*		
	(0.0113)	*(0.0236)*	*(0.0029)*	*(0.0144)*	*(0.0012)*		
TY_{t+1}	-0.0372	0.0144	0.9138	-0.0006	0.0717	86.38	1457.21
	[0.0959]	*[0.1639]*	*[0.0131]*	*[0.0003]*	*[0.0275]*		
	(0.0663)	*(0.1210)*	*(0.0150)*	*(0.0742)*	*(0.0076)*		
PE_{t+1}	0.0237	0.5164	0.0010	0.9923	-0.0028	99.06	24258.38
	[0.0128]	*[0.0218]*	*[0.0017]*	*[0.0033]*	*[0.0036]*		
	(0.0079)	*(0.0156)*	*(0.0019)*	*(0.0095)*	*(0.0009)*		
VS_{t+1}	0.0166	-0.0062	-0.0006	-0.0009	0.9916	98.27	13126.80
	[0.0170]	*[0.0290]*	*[0.0023]*	*[0.0044]*	*[0.0048]*		
	(0.0103)	*(0.0211)*	*(0.0026)*	*(0.0127)*	*(0.0011)*		

Table 5: Cash-flow and discount-rate news for the market portfolio

The table shows the properties of cash-flow news (N_{CF}) and discount-rate news (N_{DR}) implied by the VAR model of Table 2. The upper-left section of the table shows the covariance matrix of the news terms. The upper-right section shows the correlation matrix of the news terms with standard deviations on the diagonal. The lower-left section shows the correlation of shocks to individual state variables with the news terms. The lower right section shows the functions $\left(e1'+e1'\lambda, e1'\lambda\right)$ that map the state-variable shocks to cash-flow and discount-rate news. We define $\lambda \equiv \rho\Gamma\left(I-\rho\Gamma\right)^{-1}$, where Γ is the estimated VAR transition matrix from Table 2 and ρ is set to 0.95 per annum. $R^e_{M,t}$ is the excess log return on the CRSP value-weight index, TY_t is the term yield spread, PE_t is the price-earnings ratio, and VS_t is the small-stock value spread. Bootstrap standard errors (in parentheses) are computed from 2500 simulated realizations.

News covariance	N^{US}_{CF}	N^{US}_{DR}	News corr/std	N^{US}_{CF}	N^{US}_{DR}
N^{US}_{CF}	0.0007	0.0000	N^{US}_{CF}	0.0262	0.0359
	(0.0001)	*(0.0001)*		*(0.0012)*	*(0.0600)*
N^{US}_{DR}	0.0000	0.0023	N^{US}_{DR}	0.0359	0.0484
	(0.0001)	*(0.0002)*		*(0.0600)*	*(0.0019)*
Shock correlations	N^{US}_{CF}	N^{US}_{DR}	**Functions**	N^{US}_{CF}	N^{US}_{DR}
$R^e_{M,t}$ shock	0.4451	-0.8647	$R^e_{M,t}$ shock	0.6358	-0.3642
	(0.0515)	*(0.0118)*			
TY_t shock	0.1138	0.0540	TY_t shock	0.0284	0.0284
	(0.0345)	*(0.0359)*			
PE_t shock	-0.0081	-0.0885	PE_t shock	-0.8293	-0.8293
	(0.0509)	*(0.0474)*			
VS_t shock	-0.0581	-0.0253	VS_t shock	-0.2688	-0.2688
	(0.0444)	*(0.0436)*			

Table 6: Total, cash-flow and discount-rate betas

Panel A: Total beta with respect to US market

	TOTAL BETA				
	Full sample	1970s	1980s	1990s	2000s
Austria	0.24	0.15	0.24	0.38	0.27
Belgium	0.52	0.49	0.57	0.45	0.58
Finland	1.08			1.03	1.25
France	0.73	0.74	0.70	0.63	0.997
Germany	0.58	0.29	0.50	0.64	1.09
Greece	0.64			0.58	0.67
Ireland	0.70	0.56	0.75	0.66	0.87
Italy	0.49	0.29	0.42	0.59	0.79
Luxembourg	0.48			0.22	0.91
Portugal	0.48			0.42	0.55
Spain	0.84			0.79	0.85
Netherlands	0.98	0.57	0.73	0.56	0.93
Denmark	0.49	0.40	0.48	0.42	0.79
Sweden	0.84		0.55	0.83	1.29
UK	0.75	0.88	0.80	0.59	0.73
Czech Rep	0.60			0.79	0.60
Hungary	0.88			1.37	0.82
Poland	1.14			1.63	0.91
Turkey	0.85			0.27	2.10
Norway	0.90		1.00	0.84	0.85
Switzerland	0.55	0.48	0.59	0.53	0.61
Average	0.69	0.48	0.61	0.68	0.88

Panel B: Cash-flow beta with respect to US market

	CASH-FLOW BETA				
	Full sample	1970s	1980s	1990s	2000s
Austria	0.06	0.00	0.12	0.05	0.00
Belgium	0.08	0.16	0.10	0.07	-0.01
Finland	0.07			0.11	0.01
France	0.14	0.22	0.19	0.13	-0.02
Germany	0.05	0.03	0.09	0.08	0.00
Greece	-0.03			-0.09	0.07
Ireland	0.06	0.12	0.12	0.00	-0.07
Italy	0.02	0.04	0.02	0.08	-0.09
Luxembourg	-0.05			0.02	-0.13
Portugal	0.03			0.11	-0.06
Spain	0.12			0.12	0.01
Netherlands	0.07	0.17	0.07	0.07	-0.03
Denmark	0.00	0.02	-0.03	0.04	0.00
Sweden	0.06		0.13	0.08	-0.04
UK	0.13	0.25	0.11	0.08	0.07
Czech Rep	0.11			0.16	0.04
Hungary	0.13			0.27	0.05
Poland	0.12			0.33	-0.04
Turkey	-0.09			-0.23	0.11
Norway	0.13		0.19	0.11	0.04
Switzerland	0.08	0.11	0.12	0.05	-0.01
Average	0.06	0.11	0.10	0.08	0.00

Panel C: Discount-rate beta with respect to US market

	DISCOUNT-RATE BETA				
	Full sample	1970s	1980s	1990s	2000s
Austria	0.19	0.15	0.12	0.33	0.27
Belgium	0.43	0.33	0.48	0.38	0.59
Finland	1.01			0.92	1.24
France	0.59	0.52	0.51	0.50	0.99
Germany	0.52	0.26	0.41	0.56	1.09
Greece	0.67			0.67	0.60
Ireland	0.64	0.44	0.64	0.66	0.94
Italy	0.47	0.25	0.40	0.51	0.88
Luxembourg	0.53			0.20	1.04
Portugal	0.44			0.31	0.61
Spain	0.72			0.67	0.84
Netherlands	0.61	0.40	0.65	0.49	0.96
Denmark	0.49	0.38	0.51	0.38	0.79
Sweden	0.78		0.41	0.75	1.33
UK	0.62	0.63	0.68	0.51	0.66
Czech Rep	0.49			0.62	0.56
Hungary	0.74			1.09	0.77
Poland	1.01			1.30	0.95
Turkey	0.94			0.50	1.98
Norway	0.77		0.81	0.73	0.82
Switzerland	0.47	0.37	0.47	0.47	0.62
Average	0.63	0.37	0.51	0.60	0.88

Table 7: Robustness checks

We study news and betas when alternative VAR specifications are used. We report the variances of the cash-flow news and discount-rate news, and their covariances for the equity market portfolio. We also report the magnitude and time variation of betas. In order to do so, we report average betas for the: i) 12 EMU countries, ii) 3 non-EMU but EU countries and, iii) 3 new EU countries. The plus signs indicate the state variables and sample period included in the VAR model. Excess return refers to the excess log return on the CRSP value-weight index; Term spread is the term yield spread, measured as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes; PE ratio is the log ratio of S&P500's price to S&P500's ten-year moving average of earnings; Small-stock value spread is the difference in the log book-to-market ratios of small value and small growth stocks; Dividend yield is the dividend-price ratio of the market portfolio; Value spread is the difference in the log book-to-market ratios of value and growth stocks; Book-to-market spread and Market-to-book spread are calculated following Liu and Zhang (2006); Default spread is Baa yield over Aaa yield; Treasury bill rate is the 1-month Treasury bill yield.

		Models							
		1	2	3	4	5	6	7	8
1929-2005		+		+	+	+	+	+	+
1952-2005			+						
Excess return		+	+	+	+	+	+	+	+
Term spread		+	+	+	+	+	+	+	+
PE ratio		+	+		+	+	+	+	
Small-stock value spread		+	+	+				+	
Dividend yield				+				+	+
Value spread					+				
Book-to-market spread						+			
Market-to-book spread							+		
Default spread									+
Treasury bill rate								+	+
Variance of CF		0.07%	0.05%	0.16%	0.06%	0.05%	0.05%	0.08%	0.20%
Variance of DR		0.23%	0.08%	0.10%	0.20%	0.19%	0.19%	0.22%	0.09%
Cov(CF,DR)		0.00%	-0.02%	-0.01%	-0.02%	-0.02%	-0.03%	0.00%	0.00%
12 (EMU)	Beta CF	0.05	0.23	0.51	0.11	0.14	0.10	0.19	0.61
	Beta DR	0.57	0.41	0.12	0.52	0.49	0.54	0.42	0.03
	ΔBeta CF	-196%	59%	100%	-19%	118%	745%	132%	102%
	ΔBeta DR	136%	125%	105%	129%	120%	127%	137%	46%
3 (non EMU + EU)	Beta CF	0.06	0.26	0.51	0.13	0.17	0.13	0.19	0.63
	Beta DR	0.63	0.45	0.19	0.57	0.53	0.58	0.50	0.07
	ΔBeta CF	-103%	-1%	85%	-58%	-32%	-62%	331%	76%
	ΔBeta DR	81%	88%	-34%	86%	85%	93%	54%	24%
3 (new EU)	Beta CF	0.12	0.42	0.71	0.28	0.32	0.25	0.30	0.95
	Beta DR	0.75	0.50	0.18	0.60	0.58	0.66	0.57	-0.05
	ΔBeta CF	-89%	-42%	-34%	-49%	-46%	121%	-59%	-27%
	ΔBeta DR	-22%	-27%	-33%	-24%	-26%	-38%	-25%	-1276%

Table 8: Betas when cash-flow news is directly modelled

We directly model both cash-flow news and discount-rate news using two separate VAR systems. The VAR to predict discount-rate news includes the same variables as in the benchmark case. The VAR to predict cash-flow news includes dividend growth rate, market excess return, and dividend yield. Because we directly model both cash-flow and discount-rate news, they will not add up exactly to the return news, leaving a residual component. For all three news components —cash-flow news, discount-rate news, and residual news— we present the betas. In addition, we present the cash flow beta plus the residual beta, which is equivalent to the cash flow beta if we model only the discount rate news but back out the cash flow news as the residual. We report average betas for the: i) 12 EMU countries, ii) 3 non-EMU but EU countries and, iii) 3 new EU countries.

	12 (EMU)	3 (non EMU + EU)	3 (new EU)
Beta CF*	0.45	0.15	0.51
Beta DR	0.57	0.63	0.75
Beta Residual	-0.40	-0.08	-0.39
Beta CF*+Beta Residual = Beta CF	0.05	0.06	0.12

Figure 1: Average cash-flow and discount-rate betas over time

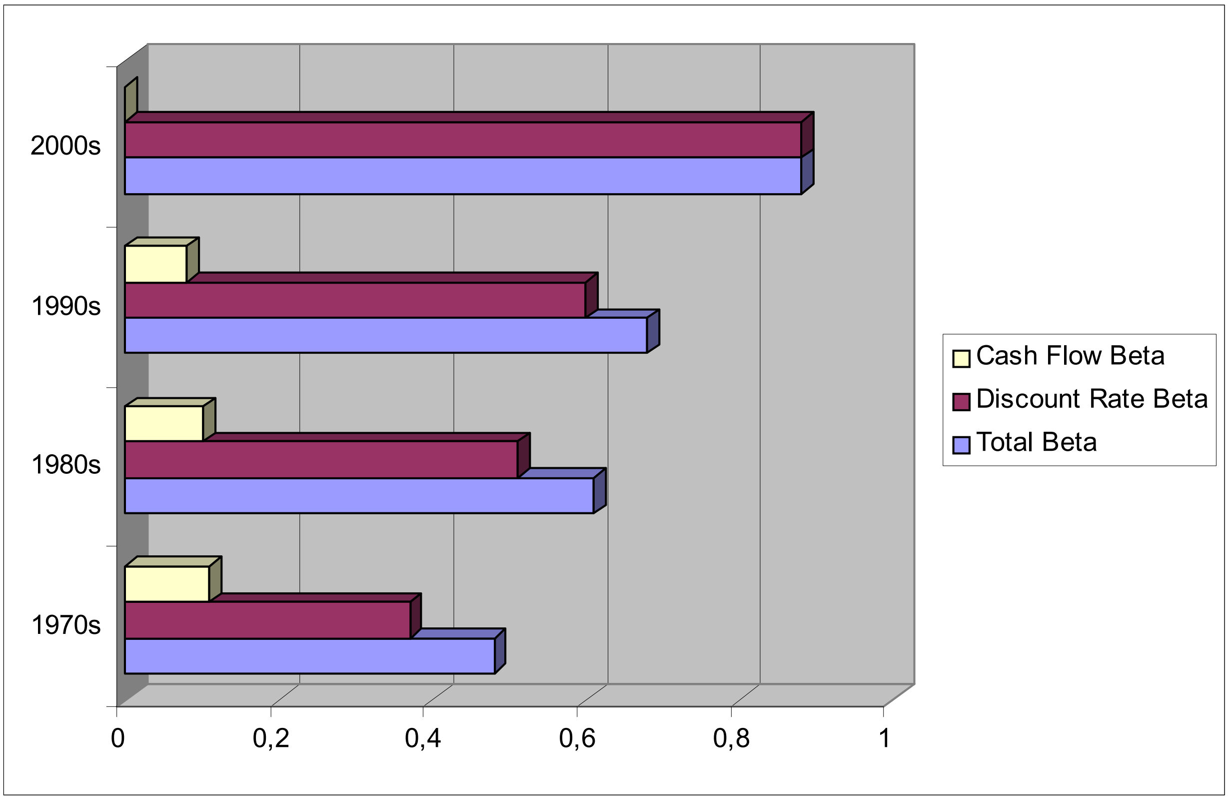
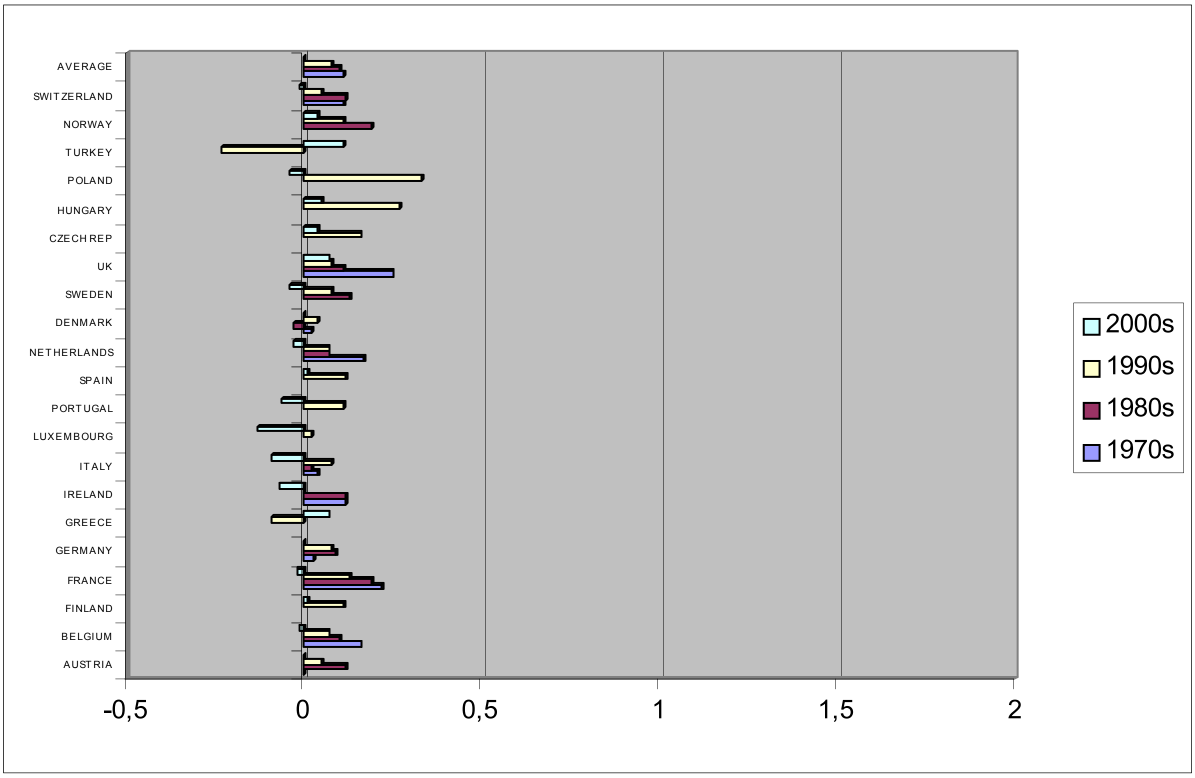
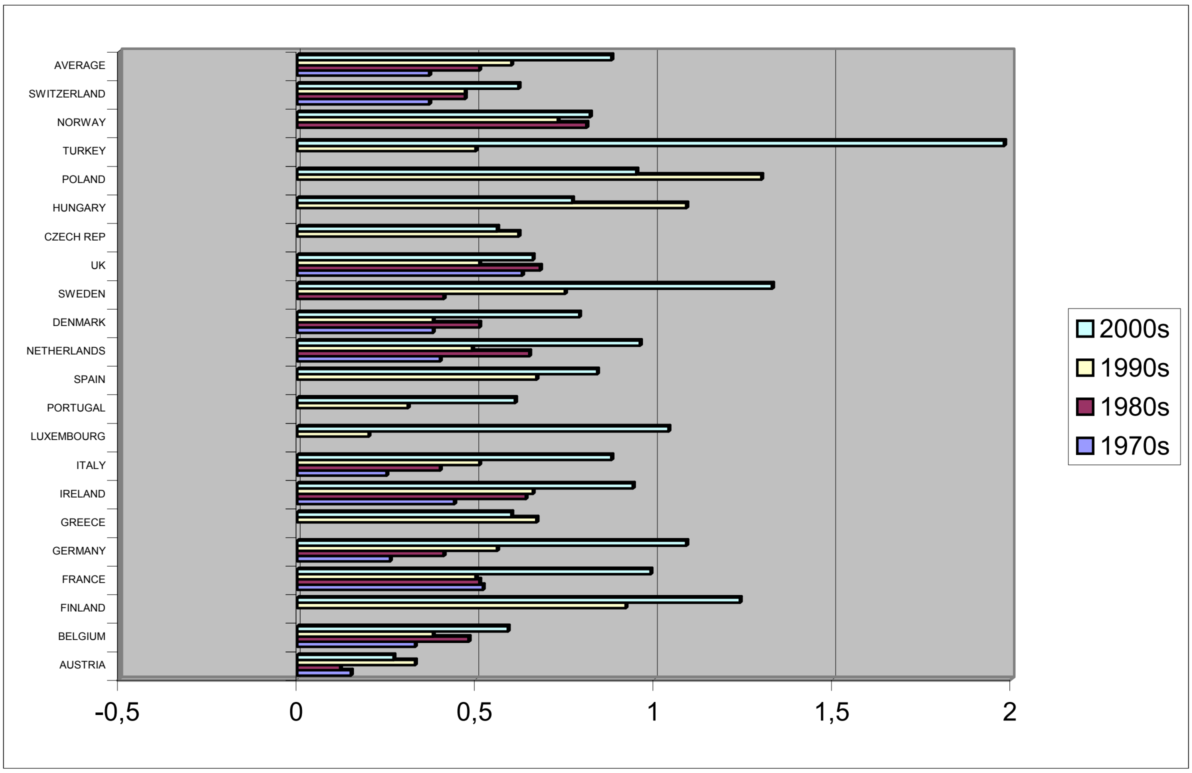


Figure 2: Cash-flow and discount-rate betas over time

Panel A: Cash-flow betas with respect to US market



Panel B: Discount-rate betas with respect to US market



CONCLUSIONS

After several years of research on volatility transmission between financial markets, many questions remain still unanswered. From a researcher's point of view, increasing availability of more complete databases, technological development, globalisation and increasing financial market integration, among other reasons, raise even more the interest in this field. From a regulator's or practitioner's point of view, understanding the volatility transmission process between markets is crucial for monetary policy, optimal resources allocation, risk measurement, capital requirements and asset valuation. Therefore, the aim of the four chapters in this dissertation is to increase the understanding of this kind of interrelation between international stock markets.

Chapter 1 is entitled "VOLATILITY TRANSMISSION MODELS: A SURVEY". Its main objective is to review the most relevant econometric methodologies applied to the analysis of volatility transmission between financial markets: GARCH models, Regime Switching models and Stochastic Volatility models. In addition, it covers several related issues such as their scope of application, the overlapping problem, the concept of efficiency and asymmetry modelling. It seems quite clear that the best methodology to be used will depend on the hypothesis to be contrasted, serving in many cases some methodologies as complementary to the others. Despite the discrepancies found in the empirical literature, some ideas seem to be shared by most of the studies. Correlation coefficients between different financial markets' returns tend to be small, positive and changing in time. It is not clear whether there is or there is not a direct or indirect relation between volatility and correlation. Furthermore, it is not clear whether this relation exists with volatility or market trend. From our point of view, markets tend to increase or reduce their common movements in periods of high volatility depending on the factors or common shocks producing them. If, as some studies suggest, the relation between contagion and volatility was always positive, portfolio diversification would not be an adequate strategy. However, if this relation depended on the existence of common factors, the existing causality should be determined and diversification across countries/regions or across industries would then be justified. What it seems quite clear is that variances, covariances and correlations contain asymmetries and are changing in time.

Finally, some guidelines for further research in volatility transmission models are given in the survey. With the increased availability of new and more complete high frequency databases, further theoretical and empirical studies will surely emerge. Multivariate SV models are particularly suited for that kind of data. However, relative to the extensive theoretical and empirical literature on GARCH models, the SV literature is still in its infancy. Therefore, further developments on multivariate SV models will be surely welcomed. Moreover, both in GARCH and SV models, additional effort should be devoted to provide realistic but parsimonious models for large dimensional systems.

Chapter 2 is entitled "VOLATILITY TRANSMISSION PATTERNS AND TERRORIST ATTACKS". The main objective of this chapter is to analyze how volatility transmission patterns are affected by stock market crises. In order to do this, we use a multivariate GARCH model and take into account both the asymmetric volatility phenomenon and the non-synchronous trading problem. In our empirical application, we focus on stock market crises as a result of terrorist attacks and analyze international volatility transmission between the US and Eurozone financial markets. In particular, an asymmetric VAR-BEKK model is estimated with daily stock market prices recorded at 15:00 GMT time for the US (S&P500 index) and Eurozone (EuroStoxx50 index). We also innovate by introducing a complementary analysis, the Asymmetric Volatility Impulse Response Functions (AVIRF) with crisis, which distinguishes both a) effects coming from a positive shock from those coming from a negative shock, and b) effects coming from periods of stability from those coming from periods of crisis.

The results confirm that there exist asymmetric volatility effects in both markets and that volatility transmission between the US and the Eurozone is bidirectional. The terrorist attack occurred in New York in September 11, 2001 affected volatility in the Eurozone stock markets but the terrorist attacks occurred in Madrid and London in March 11, 2004 and July 7, 2005, respectively, did not affect volatility in the US market. We present several possible explanations for the differences in stock market reactions to the three terrorist attacks considered. Firstly, the September 11 terrorist attack had a direct impact on several financial markets, such as the aeronautical, tourism, banking or insurance sectors. These sectors were not so badly affected in the case of the other terrorist attacks considered. Secondly, while the attacks in New York were perceived as a global shock, the attacks on Madrid and London were probably perceived as mostly having a local and regional effect, respectively. Finally, while the events of September 11 occurred in the midst of a global economic downturn, the terrorist attacks in Madrid and London occurred at a time when the world economy was growing strongly.

Chapter 3, entitled “REGION VERSUS INDUSTRY EFFECTS AND VOLATILITY TRANSMISSION”, has two main objectives. First, it analyzes the relative importance of regional versus industrial effects (as opposed to the extensively analyzed in the literature country versus industrial effects), using a wide sample including the period after the bursting of the TMT bubble. Second, it analyzes volatility transmission patterns in a particular industry across different regions. This analysis completes the information needed by portfolio managers when deciding in which regions and which industries to invest in order to diversify risks.

The results confirm the overall dominance of regional effects over industry effects. Although our findings over the whole sample time period suggest that both effects have been relatively similar in importance when determining equity returns, the pattern reveals an increasing relative importance of industrial effects only in periods of sectoral booms. In fact, the sub-periods analysis suggests that, although industry effects dominated region effects during the TMT financial crisis, region effects continue to be the most important determinant of variation in international returns. We see this evidence as suggestive that the rise in industry effects was a temporary phenomenon associated with the TMT bubble. The implications of our research for investors are that, once the TMT financial crisis is over, the traditional strategy of diversifying across countries or regions rather than industries may still be adequate in terms of reducing portfolio risk.

Complementarily, in the volatility transmission analysis, the results are suggestive of spillovers within an industry across international regions, more or less important depending on the industry being analyzed. The industries with more interaction between their second moments are Basic Industries and General Industrials. In contrast, the Information Technology industry is the less affected by other international markets. This again suggests that ignoring location aspects in the diversification strategy could be erroneous. For those practitioners whose current global strategy assumes that global equity markets remain significantly segmented, this chapter provides evidence supporting their claim. International markets may not be as integrated as it was previously believed. In fact, diversification across regions still provides greater risk reduction than diversification across industries. Of course, higher risk reduction will be achieved by diversifying both across regions and across industries, taking into account the volatility transmission patterns found.

Chapter 4 is entitled "GLOBAL VERSUS REGIONAL AND ECONOMIC VERSUS FINANCIAL INTEGRATION IN EUROPEAN STOCK MARKETS". Its first objective is to measure global and regional integration. In order to do so, we look at shock spillover intensities and proportions of variance explained by US and EU shocks for 21 local European countries. In general, shock spillover intensity has increased in time, suggesting a higher degree of both global and regional integration. The countries with higher spillover intensities from the EU are two EMU members (Greece and Belgium) and two new EU members (Poland and the Czech Republic), while the countries with higher spillover intensities from the US are non-EMU members (Turkey and Sweden). If we add up the proportions of variance explained by US and EU shocks, the three countries with a higher proportion of variance explained by international factors are France, The Netherlands and Germany, whereas Austria, the Czech Republic and Turkey are the less internationally integrated countries. In general, both the US and European markets have gained considerably in importance for individual European financial markets, though Europe has not taken over from the US as the dominant market in Europe. This would just be the case for new EU members, where the proportion of variance explained by EU shocks is larger than the one explained by US shocks.

But the main goal of this chapter is to investigate to what extent the increased exposure of 21 local European equity markets with respect to US market shocks is the result of a convergence in cash flows or a convergence in discount rates. The former would be consistent with globalization and further economic integration, the latter with further financial integration. In a first step, we decompose monthly US equity market returns into a component due to revisions in future cash flows (cash-flow news) and a component due to revisions in future discount rates (discount-rate news), using a VAR framework. Second, we confirm that betas of local European equity markets with respect to the US market have increased substantially over time. We find that this increase is nearly fully the consequence of an increase in the discount-rate beta. We see this as evidence that the increased correlation of European equity markets with global equity markets is the result of improved financial integration, and to a much lesser extent economic integration.