The Euro and Stock Market Volatility

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June 28, 2005

Abstract

This paper studies the movements of stock market volatility, for the nine European Union countries and the US, before and after the euro. I consider not only the introduction of the euro in January 1, 1999, but also the circulation of the euro notes and coins in January 1, 2002. This paper analyzes these stock markets both under segmented and integrated markets assumption. Under the segmented markets, I do not find any support for for the claim that the introduction of the euro reduces market volatility. However, the circulation of the euro notes is significant, and markets exhibit lower volatility after this date. Under the integrated markets assumption, both dates are significant for a structural break in the data.

1 Introduction:

The European Community's integration of economic affairs made major progress starting from the beginning of the 1990s. The integration started with the Single, "Common", Market which was formally completed for the existing member countries at the end of 1992. The Common market aimed to remove all the barriers to trade and to achieve free movement of goods, services, people and capital amongst the European Union (EU) member states. In the same year, the EU furthered this integration by forming the Economic and Monetary Union (EMU), which involved the introduction of a single European currency. On January 1, 1999 the euro became the new currency for eleven Member States [1] of the European Union, and after the three year transition period, during which a fixed exchange rate regime was in place and the euro served as a unit of account, physical euro notes and coins were introduced as a medium of exchange on January 1, 2002.

It is widely believed that the impact of the Single Market on EU trade was highly positive. On the other hand the introduction of a common currency has costs and benefits. The most important cost of this new monetary regime is the loss of policy flexibility in the form of monetary adjustments to idiosyncratic shocks. The benefits, on the other hand, come from eliminating potential fluctuations of exchange rates; the gains in economic efficiency that arise due to the elimination of transaction costs and fluctuations of exchange rates that give rise to uncertainty. In this paper, I will study these positive impacts of the euro on reducing stock market return volatility.

A common currency area eliminates the exchange rate risk amongst the countries involved. This decline in uncertainty reduces pricing risk for the European firms and for those investing in the European markets. In finance theory, many studies present that currency risk is a portion of the risk premium. De Santis and Gerard (1998), and Dumas and Solnik (1995) show that the currency risk is priced and ex-

[1] The eleven member states are Austria, Belgium, Germany, Spain, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Finland. By January 2001 Greece had fulfilled the convergence criteria and join the euro area.

change risk is an economically significant part of the risk premium. By the introduction of the euro the exchange risk and its portion on the risk premia is nullified amongst the euro-zone countries. Finance theory states that stock returns reflect risk premia as well as riskiness of the asset, interest rates and future dividends. Therefore, a change in the risk premium has an impact on stock market volatility.

The European Union established a formal entry criteria to the EMU by the Maastricht Treaty of 1992. This treaty underlined five monetary and fiscal convergence criterion[2] in order to qualify for participation in the EMU. One of the convergence criterion requires a candidate state to move its long-term interest rates towards the level prevailing in the three best performing EU member states. This convergence of the long-term nominal interest rates is significant in reducing the level of real interest rates. Lower real interest rates for the EMU countries increases investing in low-risk/low-return assets and which, in turn, reduces the volatility of asset value.

A common currency area has positive impacts on deeper financial integration. Hardouvelis et al (2002a) present that European equity markets became more integrated towards the end of 1990s. The euro increased financial integration, even though there were no solid regulations for deeper integration. European pension funds provide an example for such an integration. Before the monetary union, pension funds could not allocate more than 20 percent of their funds to assets denominated in foreign currency. By the launch of the euro such a restriction amongst the euro-zone is

[2]The Maastricht convergence criterion are:

1. Inflation rate no more than 1.5 percent greater than the average of the three countries with the lowest inflation rates.
2. The long-term interest rates not in excess of 2 percent above the average of the three countries with the lowest inflation rates.
3. No deviation of the currency from EUR by more then 15 percent in the two years preceding the entrance into the monetary union
4. The fiscal deficit of no more than 3 percent of GDP.
5. The ratio of general government debt to GDP of not more than 60 percent.

eliminated. Integrated financial markets allow foreign investors to have access to local securities, and this provides more diversified portfolios for these investors. Increased diversification for the EMU investors reduces the amount of risk that they bear, and this is another potential route by which the euro reduces stock market volatility.

The euro may have reduced stock market volatility also through higher efficiency in European financial markets. Financial market operations under many national currencies is a costly process and the euro improved the efficiency by nullifying such costs. Santos and Tsatsaronis (2002) show that before the introduction of the euro the underwriting fees for European corporate bonds were twice the level for the US markets, and after the introduction of the euro underwriting fees fell down to that of the US level. Higher efficiency in financial markets provides the opportunity for European investors to obtain better risk sharing portfolios cheaper and faster. Improved portfolios reduces the risk and hence the volatility in stock markets.

The previous literature on the euro studies its effects as a common currency on various economic fundamentals. Some of these studies consider possible increases in bilateral trade for the European economies after the launch of the euro. Bun and Klaassen (2002), and Micco et al.(2003) present results that support a positive impact of the euro on bilateral European trade. Some of these papers on the euro study the elimination of the currency risk from the European financial markets. De Santis et al. (2003) focus on the economic and statistical relevance of the EMU and non-EMU components of risk, and show that the elimination of the currency risk has an impact on increased market liquidity. Some of the papers focus on financial market integration, such as Hardouvelis et al. (2004) show that the integration of the European stock markets was closely related to the monetary union.

The following papers in the area study the impact of the launch of the euro on stock market volatility. Cheung and Westermann (2001) study the equity price dynamics of the German Deutscher Aktienindex (DAX) index and the US Dow Jones Industrial (DJI) index before and after the launch of the euro. Their paper indicates that the German DAX index presented a fall in volatility and persistence significant relative to that of the DJI index. Marzo (2001) and Bartram et al. (2003) argue that the introduction of the euro did not reduce volatility in all the European Stock Markets. Marzo (2001) studies the effects of the launch of the euro on European Stock Markets. Marzo's paper shows that there is an increase in the frequency of visiting high volatility regimes for the stable European markets and a decrease for the instable European markets. Bartram et al. (2003) show that the euro caused a reduction in the volatility of trade-weighted exchange rates of European countries, but an increase in stock return volatility of nonfinancial firms. Billio and Pelizzon (2003) support indeed a rise in volatility for most European stock markets. They present that both the world index volatility and the volatility spillovers from the world index and the German market increased after EMU.

In this paper, I study the change in volatility in stock market returns of the nine European Union countries, using the US as a benchmark. Empirically, the return series in financial markets data posses time-varying volatility. In order to capture this behavior, I employ a Generalized Autoregressive Conditional Heterokedasticity (GARCH) model. The GARCH model is the appropriate model in presenting conditional second moment's dependence on the previous period market shocks and on its own lagged value. I use the univariate GARCH model when considering these financial markets as segmented, and the multivariate GARCH for integrated markets assumption.

First I analyze the data under the univariate GARCH approach due to the fact that the European Union markets were less integrated in early 1990s. I examine the movements in return volatility after two shocks: January 1, 1999; and January 1, 2002. I do not find any significant evidence on lower stock market volatility by the introduction of the euro, January 1999. This lack of evidence can be due to the instability in financial and economic environment around the two year time span during which the euro was introduced. Some of the factors for such instabilities are the 1997 Asian Crisis, the 1998 Russian Crisis, the 1999-2001 oil price shocks, and the 2001 terrorist attacks to the World Trade Center. Even though the euro was launched as the common currency in January 1999, Europeans did not circulate euro notes and coins before January 2002. I find that the circulation of the euro, January 2002, has significant effects in reducing stock market volatility. Most European Stock Markets experienced a fall in return volatility after the circulation of the euro notes. The results of the empirical section show that a reduction in the volatility of the stock markets is significant after the complete transition to a common currency area, corresponding to the date January 2002.

Under the integrated markets assumption, I study the return series by employing a multivariate GARCH model. I employ such an assumption due to the fact that the European stock markets become more integrated over time. Under this specification I analyze the data for a structural break in the return series. I consider three possible break dates: January 1, 1999; September 11, 2001; and January 1, 2002. In this section, in addition to the euro effect, I analyze the effect of September 11 as a major source for instability in the economic environment. This is one of the possible candidates for blurring the January 1999 effect in the univariate case. The reason I choose September 11, rather than other major crises around 1999, is because this is one of the latest crises; and the stock markets are more integrated in the later days of the data set. The empirical results support that all three dates are significant in a break in stock market volatility.

This paper has the following structure. In section two, I discuss the data, empirical specifications, and data sources. Section three is a preliminary analysis of the return series. Section four and five discuss the characteristics of the univariate and multivariate GARCH models respectively; and the empirical results from these models. Section six concludes.

2 Data:

In this paper I study weekly market indices for the nine European Stock Markets and the Standard and Poor 500 INDEX for the United States. The weekly data set for the market indices ranges from January 2 1990 to May 17 2005. Only the US and UK stock market indexes start by January 1990. For the rest of the countries the available data starts later than 1990. Table 1 provides a brief summary about the stock market indices of these European countries and the US. The sources of these market indices are the websites of Yahoo Finance.

Amongst these nine EU countries, six of them launched the euro in January 1999 and these countries are: Austria, Belgium, Germany, France, Italy and the Netherlands. The other three European Union member countries UK, Denmark and Sweden, are not part of the monetary union. For all the stock indices in this study, stocks are weighted by market capitalization. The formula in Table 2 presents a baseline for determining the index levels.

In this study I use these adjusted stock market indices. The weekly data set for the market indices ranges from January 2 1990 to May 17 2005. However only the US and UK stock market indexes start in January 1990; for the remaining countries the available data starts later than 1990, as is indicated in Table 1. The US, Swedish and Italian stock markets closed for a week during September 11, 2001 but, excluding this date, the data is continuous for all the stock market indices.

Table 3 and Table 4 present correlation coefficient matrices of the return indices before and after the launch of the euro, January 1, 1999, respectively. Table 5 presents the correlation coefficient matrix after the circulation of euro notes and coins, January 1, 2002. All three tables indicate positive correlation coefficients amongst all the stock market return indices. Positive correlation can be evaluated as a symmetric effect of shocks on the European and US stock markets. Interestingly these tables indicate that the magnitude of correlation coefficients increase over time except those for Austrian Traded Index. After the introduction of the euro, the EMU stock markets, excluding Austria, exhibit an increase in the correlation coefficients on average of around 8 percent. After the circulation of the euro notes, EMU markets present a rise in correlation coefficients of around 28 percent. The EMU markets show higher financial integration after the circulation of the single currency. Additionally the US and UK stock markets', the biggest two financial markets in the data, correlation with other stock indices increase rapidly over time. The impact of these two financial markets on other stock indices become sounder. Last, the other two non-EMU members of the European Union, Sweden and Denmark, do not present an increasing trend in correlation coefficients after the introduction of the euro. However, after the circulation of the euro, Denmark and Sweden are more integrated with other markets, but this improvement in integration is trivial compared to the integration of EMU members.

Higher correlation coefficients indicate further market integration. Because there is lower market correlation in the early years of data and higher correlation in later years, I will study the stock markets both under segmented and integrated models. First, univariate GARCH models the data for segmented markets, and then multivariate GARCH for integrated markets.

3 Characterization of the Data:

In this section I will present a non-structural characterization of the properties of the data which may give some clues about the modeling and the error distributions of the stock market indices. The financial data often exhibit volatility clustering and leverage effects. By the existence of such effects, I will use the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to correctly represent the movements in the volatility of the return data. Time series data in financial markets often exhibit heavy-tailed and, possibly, asymmetric distributions. In the presence of heavy tails and distributional asymmetry, it is not appropriate to assume normality on the error terms of the model. These characteristics indicate that the appropriate error distribution for the univariate GARCH model is the Generalized Error Distribution (GED).

Figures 1-3 present the distribution of the price and the return series of all the stock market indices respectively. The return series are depicted for the available data set, and the range of the data for each series is given in the x-axis of the price index graphs. There are two important observations to draw from these graphs. First, the pictures indicate that there is a fall in the volatility of return series that is concurrent to the circulation of the euro bonds, January 2002. This is a very important observation and it is the focal point of this study. In the econometric part of this study, I will show that January 2002 is indeed significant in explaining the reduction in stock market volatility. The second observation to draw from these graphs is the sign of volatility clustering and leverage effect.

Volatility clustering implies that large changes in the return series are followed by large changes and small changes are followed by small changes. In other words, large returns are followed by larger returns and small returns by smaller returns. This is a symptom of the presence of autoregressive conditional heteroscedasticity, that is today's volatility depends on its previous values. As it is found in many financial time series, all the stock indices in Figures 1 - 3 display volatility clustering. In order to observe this relationship you can refer to German and Italian return series. In the German DAX index, from 1990 to the end of 1996, small changes were followed by small changes; and from 1997 to the end of 2002, large changes were followed by large changes. The Italian MIBTEL index also present volatility clustering. From 1990 to 1999, the Italian stock index exhibits large changes in stock returns; and from 1999 onwards the amplitude in stock returns are smaller.

Leverage effect means that the stock prices tend to be negatively correlated with the stock price volatility. In other words, the amplitude of a stock price fluctuation tends to increase when its price is decreasing. Looking at these graphs, it is no surprise that the high volatility periods coincide with that of a falling price. Studying the Figures 1 - 3, one can observe that in most of the return series there is a rise in the volatility of the market returns coinciding to the period when there is a fall in the market indices. One can refer to the French and Danish stock market indices to observe the leverage effect. The French FCHI index starts falling by the year 2001, and the volatility in the return series begins to increase by this date. Similarly, the Danish KFX index presents a fall in stock prices by the year 2001, concurrently there is a rise in the volatility of the Danish return series. The relationship between the volatility of the returns and the index level is important in pointing out the dependence of volatility on stock market news. The use of GARCH model will be appropriate in modeling this relationship: that is the conditional return volatility depends on market surprises.

The data analysis so far signalled symptoms of autoregressive conditional heteroskedasticity (ARCH). I will employ Engle's ARCH test to analyze the return series for any sign of conditional heteroskedasticity. You can see the results of this test in Table 6. As is presented in Table 6, at each indicated number of lags, there is indication of ARCH effects. This test supports the previous signs of autoregressive effects on volatility, and hence it is appropriate to use the Generalized ARCH (GARCH) in modeling the volatility of the return series. The GARCH will model the dependence of conditional volatility on its own lagged value, indicated by volatility clustering; and also on the market surprises, indicated by the leverage effect.

After choosing the appropriate model for volatility, next I will select the suitable distribution for the error terms of this model. Moments of the stock market indices provide a lucid framework in comparing the stock returns' distributions to a normal distribution. In this analysis, I use weekly observations ranging from January 1990 to May 2005. Table 7 presents summary statistics for the 10 stock market return series. Since the data set is composed of well-developed markets, all these markets display similar and low unconditional volatility relative to developing country stock markets. However the standard deviation is limited in determining the shape of the distribution of the return series and therefore it is useful to study the skewness and the kurtosis of the return series. These two statistics are calculated as follows:

Skewness: $\sum_{i=1}^{N} \frac{z_i^3 n}{(n-1)(n-2)}$

Kurtosis: $\left(\sum_{i=1}^{N} \frac{z_i^4 n(n+1)}{(n-1)(n-2)(n-3)}\right) - \left(\frac{3(n-1)_2}{(n-2)(n-3)}\right)$

The skewness of a distribution is a measure symmetry, or asymmetry, and the benchmark value for skewness is zero for a symmetric distribution. Referring to Table 7, we can see that the skewness of the return series range from -0.79 to 0.12. Excluding the French, Swedish and UK series, all the return series are negatively skewed, or in other words, the "long tail" is in the negative direction indicating mean $\leq$ median $\leq$ mode. That is, these stock markets give higher probability to negative returns than positive returns.

Kurtosis is a measure of the peakedness of a distribution. The standard normal distribution has a kurtosis of positive 3. A kurtosis larger than 3 indicates the distribution is more peaked than the standard normal distribution, and a value less than 3 indicates that the distribution is flatter. Table 7 demonstrates the excess kurtosis statistics of the weekly return series, and these statistics range from 0.84 to 7.85. Positive excess kurtosis indicates that all the return series have relatively peaked distribution, in other words, the values close to the mean appear more frequent than for normally distributed random variables. Higher kurtosis also signals that extreme negative and positive observations are more likely than in the normal distribution. This indicates that these markets with excess kurtosis give higher probability to extreme outliers than in the normal distribution.

After studying the third and the fourth moments of the return series, we can observe that these markets exhibit negative skewness and excess kurtosis compared to the standard normal distribution. In such a case, it is questionable to assume normality on the error term. Therefore, I will assume generalized error distribution on the error term of the univariate GARCH model. I will employ these findings in the next section, section four, solving for the univariate GARCH model.

4 The Univariate GARCH Model and Empirical Results:

As I mentioned in the previous sections, the high frequency stock market return data exhibits volatility clustering and leverage effects. These effects indicate the presence of autoregressive conditional heterokedasticity. In order to account for this, I will exploit the Generalized Autoregressive Conditional Heterokedasticity (GARCH) model as a time-series technique to model the serial dependence of volatility. Time-varying variance is the cause of heteroskedasticity: today's variance depends on the observations of the immediate past, and this is the conditional part of heteroskedasticity. The autoregressive part is a feedback mechanism that incorporates past observations into the present. GARCH modeling takes into account excess kurtosis and volatility clustering, and it provides accurate forecasts of variances and co-variances for stock market returns. In this paper I use the GARCH (1, 1) model, given by:

$$R_{it} = a_i + b_i R_{i,t-1} + c_i h_{it} + \varepsilon_{it} \quad where \;\; \varepsilon_{it}|I_{t-1} \sim GED(0, h_{it}, \nu_i) \tag{1}$$

$$h_{it} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h_{i,t-1} \tag{2}$$

In this model, i is the notation for stock market index, and t is the subscript for time. I_{t-1} is the information matrix up to and including all time t-1 information.The first equation is called the mean equation, and R_{it} is the stock market return for country i at time t. I introduce conditional variance into the mean equation, this is also denoted as Autoregressive Conditional Heterokedasticity in Mean (ARCH-in-Mean) modeling. Often, the ARCH-in-Mean model is employed where the expected return on an asset is related to the expected asset risk, and the coefficient on this term is considered as a measure of the risk-return tradeoff. The second equation is the conditional variance equation. The second term in the variance equation stands for the autoregressive part (AR), and the third for the moving average (MA). Since there is only one lagged term for the AR part and one for the MA, this is called the GARCH (1, 1) modeling. I choose the GARCH (1, 1) model rather than a more generalized model; because the additional AR and MA terms do not contribute much to the interpretation of conditional volatility. Additionally, the calculations are easier with a simpler model. Last, I assume that the error follows the Generalized Error Distribution (GED) due to the analysis in section three. Omitting the time subscript, GED is given as follows

$$f(\varepsilon_t) = \frac{\nu \, exp[-(1/2) \, |\varepsilon_t \, h_t^{-1/2} / \lambda|^{\nu}]}{\lambda \, 2^{[(\nu+1)/\nu]} \, \Gamma(1/\nu)} \tag{3}$$

$$where \qquad \lambda = \left[\frac{2^{(-2/\nu)} \, \Gamma(1/\nu)}{\Gamma(3/\nu)} \right]^{1/2}$$

In order to ensure that the above modeling provides a reasonable description of the conditional stock market variance, I look at the Ljung-Box-Pierce Q-Test. The test results are presented in Table 8. The Ljung-Box-Pierce test examines the data for serial correlation of standardized residuals at the specified lags. If there is any correlation left, this implies that the specified GARCH (1, 1) modeling does not capture those series well. Looking at the test results, there is no serial correlation at the tenth, fifteenth and twentieth lags.

I use the maximum likelihood estimator method in solving for the coefficients of equations (1) and (2). On the basis of the argument presented, the likelihood is proportional to the probability of obtaining the data as a function of the parameters. When solving for the parameters, I computed the quasi-maximum likelihood (QML) covariances and standard errors. In the financial data, often the residuals are not conditionally normally distributed. Due to this evidence, in order to obtain consistent covariance matrices, I calculate the heteroskedasticity consistent covariance matrices. Table 9 provides the parameter estimates of the GARCH (1, 1) model with a moving average term. In the table, *, ** and *** denote the significance level at the 10%, 5% and 1% levels. Except the AR term for Italy, all the coefficients for the GARCH (1, 1) specification are statistically significant at least at the five percent significance level. The estimated coefficient for the moving average term is significantly larger than the one for AR term. This indicates that the conditional market return volatility is considerable less affected by market surprises than market risk. The coefficient of the moving average term in the mean equation is statistically insignificant in all the return series except Belgium. Due to this insignificance, I will drop the moving average term in the rest of the regression analysis including for Belgium.

Next, I will analyze the coefficients first under 1999 specification, and then under 2002 specification. In the first specification, I estimate the GARCH (1, 1) model without the moving-average term for two sub-periods: before January 1999 and after January 1999. Table 10 provides the estimated coefficients for these two groups. The coefficients in the first row correspond to the observations before the launch of the euro, and those in the second row correspond to the observations after the launch of the euro. Except the coefficient for the AR term of Italy, all the GARCH (1, 1) coefficients are statistically significant. In this table, I calculated the implied unconditional volatility, measured by $w/(1 - alpha - beta)$. I derived this term by taking the lag operator of the conditional volatility in equation (2). After employing the lag operator, the estimated volatility of the underlying stock return is constant, in other words, volatility does not vary over time any more. Therefore, one can say that, the implied unconditional volatility is the forecast of the average volatility that is implicit in investors expectations. However, for the January 1999 effect, the measure for unconditional volatility does not provide any coherent results for the comparison of the two sub-periods. It is unclear to say whether the unconditional volatility increased or decreased after the launch of the euro. Looking at Table 10, one can see that the implied volatility decreased for six of the countries, but only two of these countries, Austria and Italy, are in the euro-zone. The January 1999, launch of the euro, effect on stock market volatility is unclear. The two year time span around the introduction of the euro was a turbulent period in the financial markets. The impact of the introduction of the euro on return volatility could have been over run by other fundamental economic/financial events that have happened during this period, such as the 1998 Russian crisis, or the 2000 high-tech boom.

Even though the European Union launched the euro in January 1999, the circulation of the physical euro notes and coins did not occur before January 2002. Considering that, I run the same regression as in Table 10, but this time I divide the data based on the date January 2002. The estimated coefficients for these regressions are presented in Table 11. The first row in the table stands for the estimated coefficients of the sub-period before the circulation of the euro notes, and the second row is for the coefficients for the sub-period after the circulation of the euro notes. Except for Italy, all the estimated coefficients of the GARCH (1, 1) specification are statistically significant. I calculate the implied unconditional volatility using the same measure as it is in Table 10. Unlike Table 10, the unconditional volatility provides a lucid picture. The volatility of the stock market indices of all the euro-zone countries fell after the circulation of the euro notes, except that of Belgium. For the non-euro-zone countries, the UK and Sweden also experienced a fall in the implied volatility. The same result is valid also for the US. The fall in volatility for the non-euro-zone countries is not a surprising result. As I mentioned under the data section, there exhibits a positive and high correlation of the return series after the circulation of the euro notes. Therefore, a fall in the volatility of Euro-zone markets can also be observed in the non-euro zone markets.

Comparing Tables 10 and 11, we can see that Table 11 provides a more clear display in the movement of the unconditional volatility for the two sub-periods. Due to this effect, I will estimate the conditional volatility equation, equation (2), including the dummy variables; one for January 1999 effect and the other one for January 2002 effect. This model is given by:

$$R_{it} = a_i + b_i\, R_{i,t-1} + \varepsilon_{it} \qquad where \;\; \varepsilon_{it}\,|I_{t-1} \sim N(0, h_{it}) \tag{4}$$

$$h_{it} = \omega_i + \alpha_i\, \varepsilon^2_{i,t-1} + \beta_i\, h_{i,t-1} + \gamma_1\, Dummy_{1999} + \gamma_2\, Dummy2002 \tag{5}$$

The regression results for this specification are presented in Table 12. Looking at the table, the estimated coefficient for the January 1999 dummy is either insignificant or positive. On the other hand, the January 2002 dummy yields negative and more significant coefficients. These results are consistent with what we observed in Tables 10 and 11. That is January 1999 does not have a clear effect for the volatility of the return series, but on the other hand, there is statistical evidence that the stock markets experienced a fall in volatility after the circulation of the euro notes in January 2002.

5 The Multivariate GARCH Model and Empirical Results:

In this section, I will look at the impacts of the introduction and the launch of the euro under integrated markets assumption. In section 2, while analyzing the data, I observed that the correlation coefficients of both the European stock markets and the US increased over time. The high and positive correlation coefficients indicate that the movements of these stock markets will have an impact on the future movement of other markets.

In order to capture the integrated markets assumption, in this section, I will employ a multivariate GARCH model. The motivation for multivariate GARCH model stems from the fact that many economic variables react to the same information. This implies that these variables have nonzero covariances conditional on the information set. I will follow Kim and Tsurumi (1999) approach in multivariate GARCH estimations. The setup of the multivariate model is as follows:

$$r_t = a + b\, r_{t-1} + \varepsilon_t \qquad where \;\; \varepsilon_t\,|\psi_{t-1} \sim N(0, H_t) \tag{6}$$

$$\text{for} \quad t \,\epsilon\, 1, 2, ..., T \;.$$

Above is the vectorial representation of the return series. In equation (6), r_t denotes the 10×1 time series return vector for time t. I denote each week in the data by t. The data starts by December 26, 1995, this is the date when data is available for each stock index. I excluded the two week period around September 11, 2001, due to the fact that the US, Italian and Swedish stock markets were closed for a week by September 11. Ψ_{t-1} is the information matrix up to and including time $t-1$. H_t is the time varying conditional covariance matrix; it is symmetric and positive definite. I assumed the normality of the error term for the multivariate case in order to simplify the estimation.

After defining the multivariate model for stock market returns, now I will parameterize the process for the conditional variances. I will denote h_{ijt} as the $(ij)^{th}$ element in the conditional covariance matrix H_t. The conditional correlation coefficient, ρ_{ijt}, between return i and j at time t can be expressed as:

$$\rho_{ijt} = \frac{h_{ijt}}{\sqrt{(h_{iit} h_{jjt}}} \qquad where \;\; -1 \leq \rho_{ijt} \leq 1 \quad for \;\forall\, t \tag{7}$$

Due to the difficulties in estimation of a multivariate GARCH model, I employ the Bollerslev's constant correlation estimator method. In this estimation procedure, I assume constant conditional correlation coefficients through time. Then, I can express the time varying conditional covariance, h_{ijt}, as:

$$h_{ijt} = \rho_{ij}\sqrt{(h_{iit}h_{jjt})} \tag{8}$$

After employing the Bollerslev's constant correlation estimator method, I can express the multivariate GARCH (1,1) parametrization of the model as:

$$\begin{aligned} Var(\varepsilon_t|\Psi_{t-1}) &= h_{iit} \\ &= \omega_i + \alpha_i\,\varepsilon_{it-1}^2 + \beta_i\,h_{iit-1} \qquad (9) \\ h_{ijt} &= \rho_{ij}\,(h_{iit}\,h_{jjt})^{\frac{1}{2}} \qquad for\ \ i \neq j \qquad (10) \end{aligned}$$

Table 13 presents the estimated parameters of multivariate GARCH for the whole sample range. In the upper part of the table, you can see the estimated coefficients of equation (12). Similar to the univariate estimations, the estimated coefficient of the ARCH term is significantly smaller than the one for the GARCH term. This indicates that unexpected changes in the previous period have relatively smaller impacts on the risk term compared to the lagged value of the risk. I calculated the implied unconditional volatility of the return series, using the same method as is in the univariate case. I derived the unconditional volatility by taking the lagged term of conditional volatility in equation (9) and this gives the formula $\omega/(1-\alpha-\beta)$. Looking at the table, one can observe that the unconditional volatility varies highly between the stock markets: from 4.90 to 34.23. Last, I refer to the estimated correlation coefficients of the multivariate model for the whole sample. The correlation coefficients are high and positive, on average the return series are correlated of around 0.6.

Under the integrated markets assumption, I will look for a structural break in the multivariate model for three time periods: January 01 1999, September 11 2001, and January 01 2002. The first and the last two dates are for the introduction and the circulation of the euro. I will also test for the September 11 effect in the stock markets to see that important economic/financial crisis have an impact on stock market volatility.

The structural break test for the multivariate model is similar to the one applied in the univariate model. I will modify equation (6) by dividing the whole period into two groups: the period before the break and after the break. The break will respectively correspond to three events: the introduction of the euro, September 11 2001, and the circulation of the euro notes and coins. I will investigate each event separately and modify equation (6) as follows:

$$r_t^i = a^i + b^i r_{t-1}^i + \varepsilon_t^i \qquad for\ i = 1\ and\ 2 \tag{11}$$

$$Var\,(\varepsilon_t^i \,|\, \Psi_{t-1}) = H_t^i \qquad for\ i = 1\ and\ 2 \tag{12}$$

In the above specification, the subscript i refers to each group, that is before and after the break. I will denote the parameters and the time length of these two groups as θ_1, θ_2, and T_1 and T_2. I will also assume that the conditional errors are independent between each group. Then I can express the log-likelihood function for group i as:

$$logL(\theta) = logL(\theta_1) + logL(\theta_2). \tag{13}$$

When testing for a structural break, under the null hypothesis I will assume constancy of parameters, $H_0 : \theta = \theta_0$, that is there is no structural break. Under the alternative hypothesis, I will assume that the parameters of the two periods are not equal. Then the likelihood ratio test for the structural break can be expressed as:

$$\begin{aligned} LR &= -2\,(logL(\theta_0) - logL(\theta)) \\ &= -2\,(logL(\theta_0) - logL(\theta_1) - logL(\theta_2)) \end{aligned} \tag{14}$$

The likelihood-ratio test rejects the null hypothesis if the value of the statistic LR is too small and how small is too small depends on the significance level of the test. If the null hypothesis is true, then LR will be asymptotically χ^2 distributed with degrees of freedom equal to the difference in dimensionality of parameters of the alternative and the null hypothesis.

First I calculated the estimated coefficients of the return series before and after January 01, 1999. Table 14 and 15 provide the estimated coefficients of equations (11) and (12) for this structural break. Looking at the estimated correlation coefficients for the pre and post-January 1999, one can observe that the correlation coefficients are higher in magnitude for the post-period sample. Comparing the unconditional volatility in the return series before and after the introduction of the euro, one can see that most of the markets experienced a fall in volatility, except three of them: the US, Sweden and Belgium. It is difficult to comment on the January 1999 effect, because there is no coherence amongst the groups that these countries belong to. The US is the benchmark country, Belgium is in the monetary union, but not Sweden. Therefore the effect of January 1999 on stock market volatility is harder to interpret.

Second, I estimated the coefficients of equations (11) and (12) for a structural break in September 11, 2001. Tables (16) and (17) provide the estimated coefficients before and after the break respectively. The reason I test for the impact of the September 11 terrorist attacks is because it is one of the latest major source of economic instability corresponding the area during which the euro was introduced. I try to choose an economic crisis corresponding to a later date, because the financial markets are more integrated over time. Therefore the spillover effects amongst the financial markets are larger. Comparing the implied unconditional volatility statistics for the pre-September 11 and post-September 11 groups, one can observe that the markets are less volatile after September 11 2002.

Last, I calculate the estimated coefficient of the multivariate modeling of the return series for two groups: before and after January 01, 2002. Tables (18) and (19) present the estimated coefficients for these two groups respectively. The circulation of the euro notes and coins provided significantly lower volatility in the univariate case. Similarly, I also observe that the unconditional volatility is lower for the post January 2002 group. All the countries except Belgium experienced a reduction in implied volatility after the circulation of the euro notes. This effect can be due to two factors. First is that the January 1999 effect was blurred due to the financial crisis corresponding to this period. After the settlement of the financial and economic environment the euro pronounced its effect, which may possibly correspond to the circulation of the euro notes. Second, people's behavior towards a common currency was shaped after the currency became tangible. De Frauwe and Mongelli (2005) consider that even the integration in the money markets has not progressed in a uniform way in the different market segments. For instance, the repo segment, the segment where market participants exchange short run liquidity against collateral, is less well integrated. Therefore the empirical evidence on lower market volatility after the circulation of the euro notes can be due to the fact that the single currency effect was the most observed right after the entrance of the tangible currency, January 2002.

Table (20) provides the Likelihood ratio test statistics for these three structural break points. The table provides the log-likelihood statistics of each group and the corresponding likelihood-ratio test statistic. Looking at the likelihood ratio statistics, I can reject the null hypothesis of constancy of parameters at the 0.1 percent significance level for all three structural break points. This shows that the launch of the euro, September 11 attack, and the circulation of the euro have all caused a change in the structure of market volatility.

6 Conclusion:

In this study, I looked at the change in the volatility of the stock markets before and after the launch of the euro. The change in volatility is important, since the economic theory suggests that the stock excess returns are affected by the volatility of that asset. The euro may reduce the stock market volatility because of the reduction of currency risk and higher efficiency factors.

I employed a Generalized Autoregressive Conditional Heteroskedasticity model to study effects of the euro on stock market volatility. After analyzing the data, I observed that market integration of the European countries was lower in early 1990s, and these stock markets became more integrated over time. Due to this evidence, I studied the data under two specifications: segmented and integrated financial markets.

Under the segmented markets assumption, I employed the univariate GARCH model. In this model, first I studied the impact of the launch of the euro, and then the impact of the circulation of the euro notes and coins. I did not find any support for a reduction in stock return volatility after the January 1999 introduction of the euro. However, I find that there is significant reduction in the implied unconditional volatility after the circulation of the euro notes in January 2002. The insignificance of the January 1999 effect can be due to the high instability of the financial environment corresponding to the period that the euro was launched. The Asian and Russian crises that lasted until the high-tech revolution, the March 2001 Japanese crisis, and the September 11 terrorist attacks are possible sources for instabilities that may over-run the January 1999 effect on return volatility.

Next, I analyzed the data under integrated financial markets assumption. For this case, I used the multivariate GARCH method. Under this method, I tested the data for a structural break in three possible dates: January 1, 1999; September 11, 2001; and January 1, 2002. Since in the univariate case I suspected that important economic/financial crises could underestimate the impact of January 1999, in the multivariate case I tested the data for such an effect. I chose September 11, because this is the last crisis corresponding to the period, and markets are more integrated over the last portion of the data. As expected, I found evidence supporting my claim that the September 11 crisis caused a structural break in the data. Also, both January 1999 and January 2002 caused structural breaks in the stock market volatility. The comparison of implied unconditional volatility for these two dates resulted in similar effects as was also found in the univariate case: the January 1999 effect is murky, on the other hand, the unconditional stock market volatility fell after the circulation of the euro notes and coins.

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Appendix:

Table 1: Stock Market Indices

Country	**Index**	**Long Name**	**Base Date**	**Base Value**	**Data Available from**
US	GSPC	Standard & Poor's 500 Stock Index	NA	100	Jan 02 1992
UK	FTSE	Financial Times Stock Exchange 100 Index	Dec 31 1983	1000	Jan 02 1992
Sweden	SXSAPI	Stockholm Stock Exchange SX-16 Index	Dec 31 1979	100	Dec 26 1995
Netherlands	AEX	Amsterdam European Options Exchange Index AEX	1983	100	Oct 12 1992
Italy	MIBTEL	Milano Italia Borsa Index	Jan. 03 1994	10,000	Jul 19 1993
German	GDAXI	Deutscher Aktienindex DAX	Dec. 30 1987	1,000	Nov 26 1990
France	FCHI	CAC-40 Index	Dec 30 1987	1,000	Feb 26 1990
Denmark	KFX	Kbenhavns Fondsbrs Index	July 3 1989	100	Jan 25 1993
Belgium	BFX	Brussels Bel-20 Share Index	NA	NA	Apr 8 1991
Austria	ATX	Austrian Traded Index ATX	Jan. 2 1991	1,000	Nov 9 1992

Table 2: Index Values

$$\textbf{Index Level} = \frac{\text{Current Market Value}}{\text{Adjusted Base Period Market Value}} \times \text{Base Value}$$

$$\textbf{Adjusted Base Period Market Value} = \frac{\text{Current Market Value After Adjustments}}{\text{Current Market Value Before Adjustments}} \times \text{Previous Base Period Market Value}$$

Table 3: Correlation Matrix for the Years 1990-1998

	USA	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
US	1	0.53	0.65	0.58	0.37	0.49	0.49	0.33	0.42	0.36
UK	0.53	1	0.65	0.71	0.45	0.61	0.63	0.49	0.55	0.50
Sweden	0.65	0.65	1	0.74	0.68	0.77	0.72	0.58	0.60	0.55
Netherlands	0.58	0.71	0.74	1	0.51	0.77	0.72	0.56	0.70	0.57
Italy	0.37	0.45	0.68	0.51	1	0.55	0.57	0.48	0.45	0.33
Germany	0.49	0.61	0.77	0.77	0.55	1	0.70	0.54	0.66	0.59
France	0.49	0.63	0.72	0.72	0.57	0.70	1	0.42	0.61	0.49
Denmark	0.33	0.49	0.58	0.56	0.48	0.54	0.42	1	0.46	0.41
Belgium	0.42	0.55	0.60	0.70	0.45	0.66	0.61	0.46	1	0.55
Austria	0.36	0.50	0.55	0.57	0.33	0.59	0.49	0.41	0.55	1

Table 4: Correlation Matrix for the Years 1999-2005

	USA	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
US	1	0.72	0.70	0.70	0.67	0.75	0.77	0.47	0.53	0.28
UK	0.72	1	0.69	0.81	0.71	0.78	0.83	0.58	0.67	0.34
Sweden	0.70	0.69	1	0.73	0.74	0.79	0.80	0.62	0.50	0.26
Netherlands	0.70	0.81	0.73	1	0.79	0.87	0.89	0.60	0.79	0.35
Italy	0.67	0.71	0.74	0.79	1	0.80	0.83	0.51	0.58	0.30
Germany	0.75	0.78	0.79	0.87	0.80	1	0.87	0.58	0.68	0.35
France	0.77	0.83	0.80	0.89	0.83	0.87	1	0.60	0.70	0.29
Denmark	0.47	0.58	0.62	0.60	0.51	0.58	0.60	1	0.49	0.30
Belgium	0.53	0.67	0.50	0.79	0.58	0.68	0.70	0.49	1	0.36
Austria	0.28	0.34	0.26	0.35	0.30	0.35	0.29	0.30	0.36	1

Table 5: Correlation Matrix for the Years 2002-2005

	USA	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
US	1	0.79	0.70	0.74	0.78	0.81	0.80	0.51	0.62	0.27
UK	0.79	1	0.72	0.85	0.82	0.80	0.87	0.59	0.79	0.28
Sweden	0.70	0.72	1	0.78	0.78	0.82	0.82	0.73	0.69	0.37
Netherlands	0.74	0.85	0.78	1	0.87	0.86	0.94	0.63	0.87	0.31
Italy	0.78	0.82	0.78	0.87	1	0.86	0.90	0.57	0.77	0.28
Germany	0.81	0.80	0.82	0.86	0.86	1	0.89	0.60	0.76	0.31
France	0.80	0.87	0.82	0.94	0.90	0.89	1	0.62	0.85	0.27
Denmark	0.51	0.59	0.73	0.63	0.57	0.60	0.62	1	0.60	0.39
Belgium	0.62	0.79	0.69	0.87	0.77	0.76	0.85	0.60	1	0.31
Austria	0.27	0.28	0.37	0.31	0.28	0.31	0.27	0.39	0.31	1

Table 6: Engle ARCH Test

Number of Lags	**H**	**p-value**	**Statistic**	**Critical Value**
10	1	0.00	56.99	18.31
15	1	0.00	66.37	24.99
20	1	0.00	74.87	31.41

Table 7: Summary Statistics for the Stock Market Return Series

Country	**Mean**	**Median**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
US	0.17	0.27	2.11	-0.31	2.32	-11.05	7.50
UK	0.11	0.15	2.14	0.12	1.74	-8.48	10.59
Sweden	0.21	0.46	2.99	0.01	3.29	-11.83	18.33
Netherlands	0.20	0.42	2.86	-0.33	2.92	-12.25	14.55
Italy	0.16	0.24	2.93	-0.79	7.85	-23.50	15.12
Germany	0.19	0.30	3.03	-0.08	2.05	-13.13	13.76
France	0.14	0.13	2.80	0.01	0.91	-11.42	11.67
Denmark	0.23	0.27	2.32	-0.39	1.67	-12.42	8.43
Belgium	0.15	0.29	2.36	-0.04	3.60	-9.80	13.78
Austria	0.22	0.30	2.29	-0.28	0.84	-9.84	7.19

Table 8: Ljung-Box-Pierce Q-Test

Number of Lags	**H**	**p-value**	**Statistic**	**Critical Value**
10	0	0.2745	12.16	18.31
15	0	0.3925	15.84	24.99
20	0	0.6457	17.11	31.41

Table 9:

		ai	*bi*	*ci*	*wi*	α	β	*Log-Likelihood*
		Quasi-maximum likelihood estimates						
euro zone	*Austria*	-0.08	0.08**	0.07	0.34	0.07**	0.86***	-1443.58
	Belgium	0.02	-0.01	0.05*	0.51***	0.21***	0.70***	-1590.48
	France	-0.09	-0.03	0.04	0.25***	0.11***	0.86***	-1896.19
	Germany	0.17	-0.03	0.02	0.20***	0.11***	0.86***	-1819.04
	Italy	-0.73	0.11	0.10	1.79	0.18	0.67***	-1079.91
	Netherlands	0.32***	0.00	0.01	0.14**	0.18***	0.81***	-1508.75
non-euro zone	*Denmark*	0.44***	0.05	-0.03	0.04	0.07***	0.93***	-1421.61
	Sweden	0.68***	-0.02	-0.02	0.39	0.29***	0.71***	-722.87
	UK	0.11**	-0.06	0.03	0.10**	0.09***	0.89***	-1702.86
	US	0.19*	-0.14***	0.03	0.04	0.12***	0.88***	-1250.87

Regression results for Italy, Sweden and US start from the first available data to 9/01/2001. Stock markets of the three countries closed for a week during the September 11 week. In order to estimate the GARCH coefficients the sample should be continous. Due to this restriction, sample length for these countries are shorter.

Table 10:

1999 Launch of the Euro and Structural Changes

		ai	*bi*	*wi*	α	β	*Implied Unconditional Volatility*
euro zone	*Austria*	0.19	0.09	0.28	0.08**	0.88***	7.00
		0.28***	0.07	1.08*	0.05	0.68***	4.00
	Belgium	0.20*	0.04	0.26	0.13***	0.80***	3.71
		0.16	-0.06	0.87***	0.28***	0.616***	8.37
	France	0.21*	0.01	0.36	0.08***	0.87***	7.20
		0.19	-0.11*	0.11	0.14***	0.85***	11.00
	Germany	0.37***	-0.04	0.21*	0.10***	0.87***	7.00
		0.16	-0.04	0.32	0.16***	0.82***	16.00
	Italy	0.29*	0.10*	0.21	0.04	0.95***	30.15
		-0.04	0.15	2.22	0.54***	0.32*	15.86
	Netherlands	0.47***	0.02	0.08	0.19***	0.82***	-8.10
		0.05	-0.06	0.52*	0.19***	0.77***	13.00
non-euro zone	*Denmark*	0.33***	0.11*	0.04**	0.09***	0.91***	40.00
		0.24*	0.00*	1.39	0.15***	0.64***	6.62
	Sweden	0.85***	-0.05	0.67	0.34***	0.59***	9.50
		0.18	-0.01	0.22	0.21*	0.8***	-22.00
	UK	0.29***	-0.08	0.06	0.07***	0.92***	6.24
		0.05	-0.05	0.30	0.17	0.78	6.00
	US	0.31***	-0.13***	0.07	0.11***	0.87***	3.50
		-0.10	-0.20*	1.89	0.18**	0.63***	9.64

Regression results for Italy, Sweden and US start from the first available data to 9/01/2001. Stock markets of the three countries closed for a week during the September 11 week. In order to estimate the GARCH coefficients the sample the three should be continous. Due to this restriction, sample length for these countries are shorter.

Table 11:

2002 Circulation of the Euro Notes and Structural Changes

		ai	bi	wi	α	β	Implied Unconditional Volatility
euro zone	Austria	0.13	0.07	0.34*	0.07***	0.87***	5.47
		0.49***	0.05	0.21***	-0.08***	1.02***	3.43
	Belgium	0.15*	0.00	0.63***	0.22***	0.66***	5.20
		0.35**	-0.03	0.19	0.19***	0.79***	9.00
	France	0.20*	-0.02	0.57**	0.10***	0.83***	7.86
		0.24	-0.09	0.07	0.12*	0.87***	5.48
	Germany	0.34***	-0.04	0.26**	0.12***	0.85***	8.50
		0.22	-0.02	0.06	0.11**	0.89***	8.14
	Italy	0.22	0.10*	7.99***	0.24***	-0.02	10.20
		0.19	0.08	0.03	0.06	0.93***	2.24
	Netherlands	0.40***	-0.01	0.12	0.18***	0.82***	197.69
		0.10	0.00	0.15	0.15**	0.84***	21.36
non-euro zone	Denmark	0.33***	0.06	0.03	0.08***	0.91***	5.33
		0.24	0.03	0.20	0.08*	0.884***	5.77
	Sweden	0.57***	-0.02	0.38	0.26***	0.72***	25.40
		0.30	0.02	0.23	0.11**	0.85***	6.76
	UK	0.23***	-0.08**	0.08	0.07***	0.92***	5.47
		0.15	0.03	0.14	0.18***	0.79***	4.90
	US	0.28***	-0.14***	0.05	0.11***	0.89***	8.00
		0.17	0.02	0.13	0.08**	0.89***	4.63

Table 12: Estimated Coefficients of the Univariate Model with the Dummy Variables

		ai	bi	wi	α	β	Dummy 99	Dummy 02	Log-Likelihood
euro zone	Austria	0.25***	0.08**	0.46**	0.07***	0.85***	-0.05	-0.09	-1442.50
	Belgium	0.20***	0.00	0.37***	0.20***	0.72***	0.45***	-0.42***	-1586.05
	France	0.20**	-0.03***	0.33***	010***	0.86***	0.16	-0.35**	-1893.61
	Germany	0.31***	-0.03***	0.22***	0.11***	0.86	0.31*	-0.36	-1817.45
	Italy	0.18*	0.10**	0.94***	0.13***	0.80***	-0.21	-0.50***	-1487.43
	Netherlands	0.35***	-0.01	0.14**	0.18***	0.80***	0.29*	-0.21	-1504.74
non-euro zone	Denmark	0.31***	0.06	0.08	0.07***	0.91***	0.17*	-0.14*	-1420.42
	Sweden	0.47***	0.00	0.33*	0.20***	0.76***	0.29	-0.24	-1171.36
	UK	0.21***	-0.06	0.13**	0.08***	0.89***	0.12	-0.18**	-1700.40
	US	0.26***	-0.11***	0.07**	0.08***	0.89***	0.25**	-0.22**	-1655.76

Table 13: Estimated Coefficients of the Multivariate GARCH for the Whole Sample

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.25	0.11	0.34	0.35	0.30	0.19	0.09	0.07	0.68	0.23
α_i	0.11	0.11	0.20	0.20	0.22	0.16	0.13	0.09	0.21	0.07
β_i	0.85	0.88	0.78	0.78	0.77	0.84	0.87	0.90	0.70	0.89
Unconditional Volatility	6.55	5.96	12.07	15.94	34.23	31.42	21.02	10.56	7.20	4.90
					Correlation Coefficients					
US	1									
UK	0.68	1								
Sweden	0.68	0.69	1							
Netherlands	0.70	0.76	0.74	1						
Italy	0.62	0.65	0.68	0.73	1					
Germany	0.71	0.73	0.77	0.83	0.73	1				
France	0.72	0.78	0.77	0.84	0.77	0.83	1			
Denmark	0.47	0.55	0.61	0.56	0.50	0.55	0.56	1		
Belgium	0.53	0.63	0.56	0.72	0.60	0.66	0.67	0.45	1	
Austria	0.37	0.42	0.38	0.45	0.32	0.46	0.40	0.32	0.45	1

Log-likelihood: -9374.30

Table 14: Estimated Coefficients of the Pre-January 1999 group

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.52	0.07	0.49	0.26	0.57	0.22	0.14	0.05	0.71	0.24
α_i	0.12	0.11	0.28	0.28	0.09	0.20	0.14	0.13	0.18	0.11
β_i	0.77	0.89	0.67	0.72	0.87	0.80	0.86	0.87	0.71	0.85
Unconditional Volatility	4.76	24.87	9.64	2568.00	12.27	40.69	27.33	7.38	6.19	7.24

Correlation Coefficients

US	1									
UK	0.60	1								
Sweden	0.65	0.65	1							
Netherlands	0.62	0.70	0.70	1						
Italy	0.49	0.48	0.62	0.51	1					
Germany	0.61	0.65	0.69	0.72	0.57	1				
France	0.63	0.69	0.71	0.73	0.63	0.76	1			
Denmark	0.45	0.55	0.57	0.57	0.51	0.56	0.52	1		
Belgium	0.51	0.60	0.58	0.66	0.53	0.64	0.67	0.44	1	
Austria	0.46	0.53	0.51	0.61	0.37	0.62	0.55	0.39	0.56	1

Log-likelihood: -3107.90

Table 15: Estimated Coefficients of the Post-January 1999 group

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.05	0.11	0.15	0.28	1.46	0.07	0.06	0.10	0.77	1.11
α_i	0.06	0.09	0.11	0.13	0.36	0.09	0.10	0.04	0.23	0.07
β_i	0.94	0.89	0.87	0.84	0.45	0.90	0.89	0.94	0.66	0.66
Unconditional Volatility	6.64	5.26	10.84	9.95	7.68	12.75	12.78	5.65	7.39	4.15
					Correlation Coefficients					
US	1									
UK	0.71	1								
Sweden	0.69	0.71	1							
Netherlands	0.73	0.79	0.76	1						
Italy	0.67	0.74	0.72	0.84	1					
Germany	0.76	0.77	0.80	0.87	0.81	1				
France	0.77	0.82	0.80	0.89	0.84	0.87	1			
Denmark	0.48	0.54	0.62	0.56	0.51	0.55	0.57	1		
Belgium	0.54	0.64	0.55	0.74	0.62	0.66	0.67	0.45	1	
Austria	0.34	0.36	0.32	0.38	0.28	0.39	0.34	0.28	0.39	1

Loglikelihood: -6143.30

Table 16: Estimated Coefficients of the Pre-September 11 group

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.73	0.16	0.35	0.41	2.96	0.24	0.49	0.05	1.17	0.30
α_i	0.17	0.09	0.27	0.24	0.37	0.18	0.14	0.11	0.22	0.08
β_i	0.74	0.89	0.73	0.75	0.40	0.82	0.82	0.89	0.62	0.87
Unconditional Volatility	7.82	6.99	217.06	30.42	12.96	52.96	12.11	132.50	7.46	5.92
					Correlation Coefficients					
US	1									
UK	0.65	1								
Sweden	0.67	0.68	1							
Netherlands	0.67	0.73	0.71	1						
Italy	0.55	0.59	0.65	0.66	1					
Germany	0.66	0.69	0.73	0.80	0.67	1				
France	0.69	0.73	0.74	0.79	0.72	0.80	1			
Denmark	0.45	0.53	0.55	0.54	0.49	0.53	0.52	1		
Belgium	0.51	0.57	0.50	0.66	0.51	0.61	0.60	0.37	1	
Austria	0.41	0.48	0.37	0.50	0.35	0.51	0.44	0.29	0.50	1
					Loglikelihood: -5996.30					

Table 17: Estimated Coefficients of the Post-September 11 group

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.08	0.14	0.07	0.07	0.00	0.02	0.05	0.11	0.18	3.14
α_i	0.06	0.16	0.07	0.11	0.06	0.08	0.10	0.05	0.17	0.03
β_i	0.92	0.81	0.92	0.88	0.94	0.91	0.89	0.93	0.80	0.06
Unconditional Volatility	4.02	4.60	4.83	8.57	0.33	3.27	4.59	5.22	7.70	3.46
					Correlation Coefficients					
US	1									
UK	0.75	1								
Sweden	0.69	0.73	1							
Netherlands	0.74	0.84	0.79	1						
Italy	0.73	0.80	0.77	0.86	1					
Germany	0.80	0.80	0.84	0.87	0.87	1				
France	0.78	0.88	0.83	0.94	0.89	0.90	1			
Denmark	0.50	0.58	0.71	0.61	0.55	0.59	0.63	1		
Belgium	0.56	0.75	0.65	0.82	0.73	0.73	0.79	0.58	1	
Austria	0.26	0.29	0.40	0.38	0.30	0.36	0.33	0.38	0.34	1
					Loglikelihood: -3153.90					

Table 18: Estimated Coefficients of the Pre-January 2002 group

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.99	0.18	0.37	0.50	3.69	0.28	0.58	0.05	1.33	0.27
α_i	0.16	0.08	0.26	0.22	0.36	0.17	0.12	0.11	0.22	0.08
β_i	0.70	0.89	0.73	0.75	0.32	0.82	0.82	0.89	0.59	0.88
Unconditional Volatility	6.79	5.91	24.99	13.04	11.48	34.56	10.19	12.02	7.04	5.65
				Correlation Coefficients						
US	1									
UK	0.66	1								
Sweden	0.68	0.68	1							
Netherlands	0.68	0.73	0.72	1						
Italy	0.56	0.60	0.66	0.67	1					
Germany	0.68	0.70	0.74	0.81	0.68	1				
France	0.70	0.74	0.75	0.79	0.73	0.81	1			
Denmark	0.46	0.54	0.56	0.55	0.51	0.54	0.53	1		
Belgium	0.51	0.57	0.49	0.66	0.51	0.61	0.60	0.39	1	
Austria	0.40	0.4721	0.37	0.50	0.34	0.50	0.44	0.29	0.49	1
				Loglikelihood: -6286.60						

Table 19: Estimated Coefficients of the Pre-January 2002 group

	US	**UK**	**Sweden**	**Netherlands**	**Italy**	**Germany**	**France**	**Denmark**	**Belgium**	**Austria**
ω_i	0.08	0.16	0.08	0.07	0.03	0.03	0.06	0.12	0.18	3.12
α_i	0.05	0.18	0.07	0.11	0.06	0.08	0.10	0.06	0.18	0.03
β_i	0.93	0.79	0.92	0.88	0.93	0.91	0.89	0.92	0.80	0.08
Unconditional Volatility	3.81	5.01	4.78	9.39	2.20	3.65	4.70	5.36	8.32	3.49
					Correlation Coefficients					
US	1									
UK	0.73	1								
Sweden	0.67	0.71	1							
Netherlands	0.73	0.84	0.79	1						
Italy	0.74	0.80	0.76	0.86	1					
Germany	0.79	0.79	0.83	0.88	0.86	1				
France	0.77	0.87	0.82	0.95	0.90	0.90	1			
Denmark	0.47	0.57	0.72	0.60	0.53	0.58	0.61	1		
Belgium	0.55	0.75	0.67	0.82	0.75	0.75	0.80	0.57	1	
Austria	0.26	0.3032	0.41	0.39	0.29	0.37	0.34	0.39	0.35	1
					Loglikelihood: -2879.10					

Table 20: Likelihood Ratio Test Statistics

	Log-likelihood	**LR**
No Break	-9374.3	
Pre-Jan99	-3107.9	246.2
Post-Jan99	-6143.3	
Pre-Sept11	-5996.3	448.2
Post-Sept11	-3153.9	
Pre-Jan02	-6282.6	425.2
Post-Jan02	-2879.1	