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Development of the ADCC model in Europe and the United States:

Analysis of the coefficient during crises, its drivers and an application to risk management

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Introduction

The risk of a dramatic Grexit has recently been averted. However, many analysts wonder if the possible third bailout will enable the country to get back to self-sufficiency. To be granted this new loan, Greece needs to implement drastic austerity measures to which the government and the people appear hostile. It has now been five years since the first bailout and it seems that history has been repeating itself. The evolution of the situation in the country highly impacted its borrowing cost and, by spillover, the other Euro area government bonds. Consequently, the robustness of the region and its resistance to new negative shocks have been called into question. The financial stability of such an area can be assessed by the presence of diversification opportunities even in financial turmoil.

Financial stability is affected by investors' reaction (Suk-Joong, Moshirian and Wu, 2005), and studying stock-bond correlation provides insight of their behaviour as changes in the coefficient represent modifications of their risk perception of the given assets. Furthermore, a deep understanding of the stock-bond return relation and its drivers allows to forecast the future stock-bond comovements. These projections then enable to define profitable strategies in risk management and asset allocation (Fleming, Kirby and Ostdiek (1998); Li (2002)).

In this study, the first section will be devoted to a literature review of the different models estimating correlation, its drivers and Flight-To-Quality and contagion episodes. The next chapter will consist in a presentation of the data and some descriptive statistics. A reliable model will then be developed in order to accurately estimate stock-bond correlation in Europe and in the United States and take into account various essential stylized facts. In section four, a deeper analysis will be applied to the stock-bond comovements during the 2007-2009 global financial crisis and the Euro area sovereign debt crisis. It will aim at identifying possible flights between the assets. We will also conduct an analysis of the behaviour of investors as to understand their motives for their shift in assets risk perception. The fifth unit will expose a method to understand the link between stock-bond correlation and various economic indicators.

Afterwards, the two last sections will be devoted to an application of stock-bond correlation to mitigate the risk exposure of a portfolio composed of equities and government bonds. To do so, in chapter six, forecasts of stock-bond correlation will be developed using the drivers set defined in the previous section as possessing the highest explanation power of the coefficient. Along with this, forecasts of the assets volatility will be produced to complete the projections of the covariance matrix. Finally, and before exposing our conclusion, the seventh section will consist in the application of the values previously forecasted to reduce the risk exposure of a portfolio. The goal will be to minimize the expected Value-at-Risk, leading to close-to-optimal Conditional Value-at-Risk solutions, and to further analyse the results in order to determine whether this strategy can be considered as producing efficient results.

1. Literature Review

a. Stock-Bond Correlation

i. Evolution of the framework

The stock-bond return relation has been investigated for a long period by academic researchers. Widely used in portfolio and risk management, the econometrical frameworks to analyse it have improved starting from the basic Pearson correlation factor up to more advanced conditional, dynamic and asymmetric correlation factors.

Developing the precepts of the modern portfolio theory, Markowitz (1952) uses correlation and covariance between assets to compute the variance of a portfolio, which he defines as an approximation of its risk. Following his model, the correlation is equal to:

$$\rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}$$

However, as found by many researchers, the methodology to compute the correlation between stock and bond returns should not considered it as a constant variable (Chiang and Li, 2009; Barsky, 1989; Fleming, Kirby and Ostdiek, 1998; Scruggs and Glabadanidis, 2003). To estimate it accurately, stock-bond correlation rather needs to be time-variable as many variable factors have an influence on its value.

By way of illustration, market conditions are one factor affecting the stock-bond returns relation (Chiang and Li, 2009). Those authors show that in good market conditions, the correlation between the two assets return tends to be positive. States of the economy also impact stock-bond comovements. Economic growth is for example expected to lead to negative correlation (Ilmanen, 2003). In the same way, Barsky (1989) identifies the level of productivity to play an important role. Additional macroeconomic variables have an impact such as inflation (Ilmanen, 2003; Bekaert and Grenadier, 2001; Mamaysky, 2002; Li, 2002) and interest rates (Chiang and Li, 2009; Li, 2002; Perego and Vermeulen, 2013). Finally, authors have found that stock-bond correlation is highly affected by uncertainty measures (Stivers and Sun, 2002; Li, 2002; Scruggs and Glabadanidis, 2003).

News about those indicators accordingly have different consequences on the valuation of stocks and bonds, and then directly affect the stock-bond correlation. For this reason, we maintain that the econometric frameworks featuring a constant correlation (see for example the constant correlation (CCORR) model of Bollerslev, 1990) will not accurately reflect the relation through time and that it should therefore not be considered at any point as a constant value.

In order to overcome this issue, researchers have developed and applied the rolling window correlation estimator (Andersson, Krylova and Vähäma, 2004; Chiang and Li, 2009). The concept is simply to define a window length that will be rolling through the time interval of the study and to compute a correlation coefficient for each window, most of the time using the same formula as Markowitz (1952), and hence giving equal weights to all the values located in the rolling window. We have for $r_{t,i}$, the return of the asset i on time t:

$$\rho_{12,t} = \frac{E_{t-1}(r_{1,t} r_{2,t})}{\sqrt{E_{t-1}(r_{1,t}^2) E_{t-1}(r_{2,t}^2)}}$$

Unfortunately, this method raises some concerns. Indeed, Andersson, Krylova and Vähäma (2004) argue that rolling correlation cannot be considered as a proper measure because it will adjust slowly to new information due to its equal weighting. Furthermore, unusually big or small return values will lead to gaps in the correlation coefficient by entering and getting out of the rolling window, giving improper signals. It has also been proved that the rolling correlation coefficient does not react properly in market stress situations (Boyer, Gibson and Loretan, 1999; Longin and Solnik, 2001; Forbes and Rigobon, 2002). It actually appears that higher volatility induced by extreme market conditions leads the rolling correlation estimator to be biased upwards. This issue, called condition bias becomes a problem when trying to accurately assess whether market turbulences have led to a flight-to-quality or contagion between the assets.

Engle (2002) identifies the exponential smoother used by RiskMetrics™ as a way to solve the problem of equal weights. This parameter uses declining weights based on a parameter λ, giving more importance to the most recent data's. The formula is the following:

$$\rho_{12,t} = \frac{(\sum_{s=1}^{t-1} \lambda^{t-s-1} * r_{1,s} * r_{2,s})}{\sqrt{(\sum_{s=1}^{t-1} \lambda^{t-s-1} * r_{1,s}^2) * ((\sum_{s=1}^{t-1} \lambda^{t-s-1} * r_{2,s}^2))}}$$

Unfortunately, this method fails to provide indications on how to determine the value of λ and on the length of the rolling window.

In order to improve the model and to overcome the problem of conditioning bias, the returns are defined as the conditional standard deviation times the standardized disturbances:

$$r_{i,t} = \sqrt{h_{i,t}}\varepsilon_{i,t} \text{ with } i = 1,2$$

By substituting the new returns in the previous formula, we find the Conditional Correlation model of Bollerslev (1990). In this model, while the variances are time varying, reflecting the changes in volatility in the two markets, the correlation coefficient is fixed through time. The changes in the variance-covariance matrix will only be the results of changes in volatility. Despite the fact that the inclusion of conditional variance is a major improvement, the constant correlation remains too restrictive for the purpose of studying stock-bond correlation.

In this regard and to overcome this issue, Engle and Kroner (1995) developed a model named BEKK whose form is:

$$\Sigma_t = C + B^T \Sigma_{t-1} B + A^T \varepsilon_{t-1} \varepsilon_{t-1}^T A$$

with C and the additional terms being positive-definite matrixes, Σ_t is guaranteed to be positive-definite as well.

While this framework is a major improvement, it requires many parameters. Consequently, the optimization will be complex and parsimonious to complete. If some restrictions on the parameters can be applied in order to tackle this problem, the model loses generality in return (Glabadanidis, 2008).

More recent studies including Engle (2002) estimate the correlation in different steps. The first step consists in modelling the volatility of each asset thanks to a process of the GARCH family. The correlation is then estimated using an exponentially smoothing function of the standardized residuals. The Dynamic Conditional Correlation (DCC) model can be viewed as a generalization of the CCORR model of Bollerslev (1990), allowing the correlation factor to be time varying. The first step of the estimation is formulated as follows:

$$\boldsymbol{r_{i,t} = \mu_i + \varepsilon_{i,t}}$$

$$\boldsymbol{\varepsilon_{i,t} \sim \mathcal{N}(0, H_i)}$$

$$\boldsymbol{h_{i,t} = c_i + a_i * \varepsilon_{i,t-1}^2 + b_i}$$

$$\boldsymbol{z_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}}$$

The conditional mean of the returns of each asset is estimated. Their volatility is also assessed employing a univariate GARCH process. By dividing the former by the latter, we get the standardized residuals. Once those have been found, the second step of the model is applied:

$$\boldsymbol{Q_t = (1 - \alpha - \beta) * \bar{Q} + \alpha\, z_{t-1} z_{t-1}' + \beta Q_{t-1}}$$

$$\boldsymbol{R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}}$$

where $\boldsymbol{\bar{Q}}$ is the unconditional covariance of the standardized residuals:

$$\boldsymbol{\bar{Q} = Cov(z_t z_t') = E[z_t z_t']}$$

This is a case of variance targeting with the unconditional covariance being the target because “the long run solution of a conditional covariance (correlation) model is given by the unconditional expectation of the dynamic conditional covariance (correlation)” (Caporin and McAleer, 2009). The $\boldsymbol{Q_t}$ are estimated for the assets variance and their covariance. In the latter formula, we recognise the expression of Markowitz (1952).

Engle (2004) has further improved his DCC model by adding the asymmetry hypothesis. The asymmetry in volatility linked to asset returns has been widely investigated and is reflected in the DCC model by allowing the GARCH process to be replaced by different volatility models, capturing the leverage effect (as we will see in section 3.a.iii.). On the contrary, asymmetric effects in correlation have not received much attention. Kroner and Ng (1998) are the first to develop a model that takes asymmetry in covariances into account. They argue that if the expected return of one asset is impacted by asymmetric volatility effect and that the expected return of the other asset is not affected, the correlation between the two assets returns should change. Some other models were introduced previously acknowledging the asymmetric effects in conditional covariances (Koutmos and Booth, 1995; Koutmos, 1996; Scruggs, 1998). However, their covariance matrixes were based on the assumption of constant conditional correlation, as in Bollerslev (1990), which is too restrictive. Furthermore, little had been done to economically explain the presence of asymmetric effects in covariance.

Engle (2004) observes two possible explanations. The first one that he identifies holds to time-varying risk premia. After a negative shock leading to higher volatility on both markets, investors would require increased expected returns, which leads to a fall in prices on both markets. That would result in higher correlation. We can then suggest that correlation will go up higher after negative innovations than after positive ones of the same magnitude. Thus, when diversification options are most needed, it is difficult to find any. However, bad news on the stock market can be followed by episodes of flight-to-quality to the perceived safer bond market, lowering the correlation between the two assets. Another way of understanding the asymmetric effects in covariance rests on the dependency of returns. Once a market is hit by negative news, it is more likely that the fall in prices of one market will be spread to other markets rather than raising prices in different markets after positive news in one of them.

To reflect those observations, Engle (2004) modified his DCC model in the Asymmetric Dynamic Conditional Correlation (ADCC) model with two different steps in the estimation process. At first:

$$\boldsymbol{r_{i,t} = \mu_i + \varepsilon_{i,t}}$$

$$\boldsymbol{\eta_{i,t} = max[0, -\varepsilon_{i,t}]}$$

$$\boldsymbol{\varepsilon_{i,t} \sim \mathcal{N}(0, H_i)}$$

$$\boldsymbol{h_{i,t} = c_i + a_i * \varepsilon_{i,t-1}^2 + b_i + d_i * \eta_{t-1}^2}$$

$$\boldsymbol{z_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}}$$

and then:

$$\boldsymbol{\lambda_{i,t} = max[0, -z_{i,t}]}$$

$$\boldsymbol{Q_t = (1 - \alpha - \beta - \gamma) * \overline{Q} + \alpha\, z_{t-1}z'_{t-1} + \beta Q_{t-1} + \gamma \lambda_{t-1}\lambda_{t-1}'}$$

$$\boldsymbol{R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}}$$

with $\boldsymbol{\overline{Q}}$ the unconditional covariance.

As we see, the ADCC model reflects the asymmetric effects in the univariate volatility models thanks to the addition of the $\boldsymbol{d * \eta}$. The asymmetry effects in the covariance are present through the $\boldsymbol{\gamma \lambda_{t-1} \lambda_{t-1}'}$, enabling the process to react differently to negative innovations.

ii. Description of the factors

As previously stated, there is a wide range of factors that hold an influence on the stock-bond correlation, among which various macroeconomic variables and uncertainty measures.

<u>Macroeconomic variables</u>

With an eye to demonstrate how the stock and bond returns can be differently impacted by news about macroeconomic factors, we introduce an affine model. If we assume the price of stocks and bonds is the present value of future cash flows, we have the following (Ilmanen, 2003):

$$\boldsymbol{P_S = E\left[\sum_{t=1}^{\infty} \left(\frac{1 + G}{1 + Y_t + ERP_t}\right)^t * D\right]}$$

$$\boldsymbol{P_B = E\left[\sum_{t=1}^{T} \frac{C_t}{(1 + Y_t)^t} + \frac{FV}{(1 + Y_T)^T}\right]}$$

Both assets are valued as the present value of their expected cash flows, which are certain for bonds and uncertain for stocks, discounted by a rate with different premiums. Stock prices are equal to the sum of expected dividends (D), accruing at constant growth rate (G), discounted by the government bond yield (Y), which is composed by the expectations of the future short-term rates and the required bond term premium.

Bond prices are worth the sum of their coupons (C) and face value (FV) discounted by the government yield (Y). Regarding the two formulas above, we can observe that variation in prices is due to changes in expectations of the future value of any of the elements that appear, which means that only news and shocks can impact them.

Comparing the two formulas enables to find out that the growth rate expectation is a source of difference of values between stocks and bonds since it is proper to stocks only. Ilmanen (2003) points out that stocks on average outperform bonds during business cycle expansions in the United States market while the inverse is noticed during contractions. On their side, Chiang and Li (2009) agree with the fact that stocks tend to perform well in economic expansions, and argue that it is due to the higher confidence of the investors in the economy, which leads them to buy more of the perceived more risky asset. However, when the economic prospects are positive, bonds coupons are generally high, which induces positive correlation. On the other hand, when the stock market crashes, investors will fear for their money and eventually invest more heavily in the perceived less risky assets, which in this case are bonds. Barsky (1989) gets similar results by identifying the productivity, generally a reliable indicator of economic growth, to have a positive relation with stock-bond correlation. Perego and Vermeulen (2013) divide Europe in Northern and Southern regions and find a negative relation between the GDP growth and stock-bond correlation in the Southern European countries whereas they get mixed results in crossed-regions market. Conversely, Andersson, Krylova and Vähämaa (2004) note that SBC does not seem to be affected by the economic growth expectations. From this analysis appears that previous literature fails to find a global consensus about the link between economic growth and stock-bond correlation.

Highly linked to GDP growth, news about expected inflation affect stocks and bonds returns differently. Indeed, while bonds are negatively impacted by higher inflation since their coupon stream is fixed, the effect on stock returns are mixed given that higher inflation will also increase the dividend stream, and hence neutralise the higher discounting factor. Shiller and Belratti (1992) argue that bonds coupon stream is nominal while stocks dividend stream is real, and thus should not suffer from inflation. However, high inflation levels will also hurt equities because of their negative effects on real earnings (Ilmanen, 2003). Also, when inflation is high, variation in discount rate pushes stocks and bonds in the same direction whilst low inflation levels tend to make discount rates more stable, and growth uncertainty dominates, lowering SBC. This hypothesis is confirmed in Europe by the study of Perego and Vermeulen (2013) and Andersson, Krylova and Vähämas (2004). Indeed, they find a positive relation between expected inflation and stock-bond correlation across different regions.

Li (2002) approves the previous results about expected inflation and goes even further. He states that stock-bond correlation is predominantly driven by the uncertainty about long-term inflation. He assumes that the lower the visibility of the investors is regarding inflation prospects, the higher the correlation coefficient between the two assets will be. He also studies the effects of unexpected inflation that is defined as the a posteriori difference between effective inflation and expected inflation. He disputes that unexpected inflation affects the stock unique component negatively, which is a "control variable for the volatility of stock returns due to the unique stock pricing factors". Eventually, he indicates that its effects are ambiguous and depend on the way dividends and real interest rates react to unexpected inflation shocks. According to Chiang and Li (2009), inflation hurts profits and causes a decline in stock returns. On the contrary, inflation is profitable for bond returns thanks to its positive impact on bond yields.

The case of deflation has not been much debated in the literature. Ilmanen (2003) argues that deflation causes higher equity risk premium and lower bond risk premium, leading to negative SBC.

As we can assume from the above formulas, news about interest rates[1] have a positive relation with stock-bond correlation. Considering the United States and United Kingdom, Shiller and Belratti (1992) find that stock and bonds are both negatively correlated with changes in long-term interest rates, which leads to higher correlation between the two assets. In this respect, Chiang and Li (2009) investigate the effects of interest rates on stock-bond correlation through monetary policy cycles and find similar results in the United States, and Perego and Vermeulen (2013) confirm the relation in the European market. As a matter of fact, monetary tightening leading to higher interest rates impact positively bond yields but surprisingly, it also benefits to stock returns thanks to the income effect (Friedman, 1969).

[1] reflected by government yield.

While the indicator does not appear explicitly in the above formulas, authors have found evidence of the effect of liquidity on the stock-bond return relation. Baele, Bekaert and Inghelbrecht (2010) even identify liquidity to be the main driver of stock-bond return comovements. They argue that shocks will not be transmitted quickly in illiquid markets, preventing any reactions and consequences on stock-bond correlation. Chiang and Li (2009) identify liquidity to positively impact the stock-bond return relation.

Uncertainty measures

Apart from the macroeconomic variables examined here above, a wide part of the literature about stock-bond comovements investigates its links with measures uncertainty. The fundamental hypothesis is that in episodes of higher uncertainty about different major economic variables, investors will look for safer assets, in this case bonds. Connolly, Stivers and Sun (2005) give a substantial sum-up of the way those elements interact in the G7 countries from 1986 to 2000. To measure stock market uncertainty, they utilize implied volatility from equity index options that are known as fear indexes on one hand and abnormal stock turnover that reflects dispersion-in-beliefs and changes in the investment opportunity set on the other hand. They find that the probability of negative correlation in coming months rises sharply following high values in their uncertainty measures. On an international point of view, they show the central role of the implied volatility of the United States stock options by proving that it has explanation power for the stock-bond correlation in the other G7 countries, excepted for Japan. And on a contemporaneous framework, they demonstrate that bond returns tend to go up relative to stock returns when uncertainty reaches higher levels.

On a similar note, Scruggs and Glabadanidis (2003) study the links between the risk premia and the covariance between stock and bond returns. Their proxy for risk factors is the excess returns of equity and bond markets. They attest evidence of volatility contagion from the bond market to the stock market. More precisely, the volatility of the stock market tends to increase more largely after bad news affecting the bond market than after positive news. The hypothesis of absence of relation between bond and stock risk premia and stock-bond correlation is thus rejected. They find that the relation between bond risk premium and stock-bond covariance is positive and significant while the relation between stock risk premium and stock-bond covariance is also positive but insignificant. However they conclude that their model fails to explain adequately the relation between stock and bond risk premia and stock-bond covariance. David and Veronesi (2001) derive uncertainty measures from surveys about future inflation and earnings growth. They conclude that these variables measure uncertainty better than their volatility. They find also that these highly improve their forecast of stock and bond returns covariance. On their side, Stivers and Sun (2002) and David and Veronesi (2002) show that implied volatility of stock index options are a relevant proxy of stock market uncertainty and feature an inverse relation with stock-bond correlation. Applying the same process in the European Monetary Union, Suk-Joong, Moshirian and Wu (2005) argue that the implied volatility of the German stock options is relevant in order to explain the stock-bond correlation of other EMU countries, with the exception of Italy. And as previously stated, uncertainty about fundamentals also appears to hold strong relations with stock-bond comovements (Chiang and Li, 2009; Li, 2002).

b. Flight-to-Quality and contagion episodes

Flight-To-Quality and contagion episodes are important topics that can be studied through the value of the correlation between stock and bond markets. Investigating these questions gives insights about the behaviours of investors in normal and extreme market conditions and directly assesses the stability of financial systems. Contagion is defined as "an increase of the correlation coefficient in a crisis period compared to a benchmark period" and flight-to-quality from stocks to bonds as "a decrease in the correlation coefficient and simultaneously falling stock markets" (Baur and Lucey, 2008). It is clear from these definitions that these events are mutually exclusive. A financial system is said to be stable if it dampens shocks rather than amplifies them (Das, 2003). In case of a crash in stock exchange, financial markets need to feature a flight-to-quality to be resilient. The decrease in the correlation coefficient, which ideally leads to negative values, enables a portfolio composed of bonds and stocks to suffer to a lower extent from the shocks in the equity market than would a portfolio whose all capital is invested in equity. On the contrary, if there is contagion between stock and bond markets, investors' portfolios, even if diversified, will experience severe losses since there is no efficient allocation of capital possible, which suggests instability of the financial system (Weber, 2008).

Gulko (2002) lists all the stock market crashes, defined as a 5% loss or more in the

S&P500 in one day, since World War II and finds that during most of them, the bond market rose, supporting the idea of flights-to-quality. He indicates that these episodes are the result of the investors adjusting their portfolio and proportionally increasing their exposition to perceived safer assets such as government bonds. He further states that the magnitude of the stock market decline is often equal to the one of the bond market rise. This suggests that government bonds provide effective portfolio diversification. The author applies the same study with corporate bonds. He argues that they have a different behaviour than government bonds since they will most of the time fall during stock market crashes, and the lower their credit rating is, the greater the decline will be.

Hartmann, Straetmans and Devries (2004) apply a different econometric framework that represents the linkages between assets by asymptotic tail dependence. This new measure is not supported by a probability law, and hence does not underestimate the tail events occurrence. Their model indicates that co-crashes happen more often than what previous studies show. They find that contagion between international stock markets happens 20% of the time. This figure is lower for bonds and even lower for co-crashes between stocks and bonds. The frequency of the latter is close to the flight-to-quality's one. These figures prove a high degree of integration between markets and authors state that on this ground, it is more and more difficult to prevent a crisis to spread among linked countries. In coherence with what was previously said, Chiang and Li (2009), Andersson, Krylova and Vähäma (2004) and Ilmanen (2003) state that flights-to-quality tend to happen when uncertainty about economic fundamentals is high.

Studying the volatility linkages between markets also enables to assess financial stability. Suk-Joong, Moshirian and Wu (2005) indicate that in case of negative news in one market, investors will increase their exposure to the perceived safe asset and thereby increasing cross-market volatility. In Eurozone markets, they note that cross-market volatility spillovers are generally unilateral implying that whereas shocks in bond market affect stock market volatility, the reverse is not true. Following the same idea, Bekaert and Wu (2000) also find evidence of cross-market volatility due to contagion effects. Finally, Perego and Vermeulen (2013) undertook to document flight-to-quality between regions in both stocks and bonds. In Europe, they observe that investors have switched from Southern to Northern markets during the sovereign-debt crisis. Indeed, fearing possible defaults of some Southern Europe countries, these investors have shifted their money to perceived safer Northern countries assets.

2. Data

The data consists of daily stock and government bonds total return indexes of the European Monetary Union and the United States. The data cover a time period of close to 14 year from January 1st 2001 to October 31st 2014. The chosen EU and United States stock indexes are the Stoxx600 and S&P500. For bonds, the studied indexes are Datastream benchmarks of 10-year government bonds. As Andersson, Krylova and Vähämaa (2004) have shown that the maturity of bond indexes has little impact on the results, we chose a maturity of 10 year due to its popularity among other studies. All the indexes are total return ones in order to take all kinds of cash flows into account.

We decided to analyse Europe as a whole instead of country by country since academic researchers widely document the high degree of integration in the European Monetary Union (Suk-Joon, Moshirian and Wu, 2005; Fratzscher, 2002). This choice enables to unambiguously compare the possible flights-to-quality and contagion episodes in the United States and in Europe, especially during the sovereign debt crisis.

Data of macroeconomic fundamentals are retrieved from Datastream. Data are most of the time monthly, excepted for expected inflation that is quarterly. We employ the cubic spline interpolation technique to convert them to monthly figures, as it is explained in section 5.a.ii. Inflation and GDP data come from Eurostat and the United States Bureau of economic analysis. Expected inflation figures are provided by the IFO World Economic Survey. The Interest rates data are offered repo rate given by Thomson Reuters. And finally, data about the implied volatility are the VDAX, as it proved to impact the EMU globally with the exception of Italy (Suk-Joong, Moshirian and Wu, 2005) and CBOE VIX indexes.

The table below gives insights of the return time series. Returns are continuously compounded using the following:

$$\boldsymbol{r_t = log\left[{}^{P_t}/_{P_{t-1}}\right]}.$$

The skewness and kurtosis are computed using the formulas:

$$\boldsymbol{Skewness} = \frac{\boldsymbol{E(r-\mu)^3}}{\boldsymbol{\sigma^3}}$$

$$\boldsymbol{Kurtosis} = \frac{\boldsymbol{E(r-\mu)^4}}{\boldsymbol{\sigma^4}}$$

with $\boldsymbol{\mu}$ the mean and $\boldsymbol{\sigma}$ the standard deviation of the returns.

The skewness and kurtosis are the third and fourth moments of the time series and give indications of the shape of the returns distribution. The standard values of these moments for the normal distribution are 0 and 3 respectively. The negative skewness featured in the four time series signifies that the tail on the loss side is fatter or longer than on the right, meaning that the loss probability would be underestimated by a normal distribution. The kurtosis gives insights about the peakedness of a distribution. A large value designates a distribution that has fat tails and a sharp peak. Unsurprisingly, we find that stock returns have larger kurtosis than bond returns. Again, the values are quite far from the standards of a normal distribution.

Descriptive statistics	Mean	Std Deviation	Max	Min	Skewness	Kurtosis
EU Stocks	0,00011	0,0126	0,0942	-0,0792	-0,1126	8,7489
US Stocks	0,0002	0,0126	0,1096	-0,0946	-0,1983	12,0631
EU Bonds	0,00024	0,0034	0,0224	-0,0149	-0,0548	4,7031
US Bonds	0,0002	0,005	0,041	-0,0276	-0,0318	5,4943

Table 2.1 Descriptive statistics

3. Modelling the Asymmetric Dynamic Conditional Correlation

As stated in the literature review, the ADCC model is estimated using a two-step approach. The first one aims at evaluating the conditional mean and the volatility of the time series involved while the second one focuses on estimating the correlation coefficient. We first concentrate on volatility modelling.

a. Stylized facts about volatility

There are many different econometric frameworks that enable to model volatility. In order to pick the one that fits the best a time series, it seems essential to first identify some stylized facts about volatility.

i. Volatility Clustering

If large movements in financial markets tend to be followed by large movements, it is equally true for small changes. This results in persistency of high and low volatility episodes, with positive and negative movements, and leads to clustering (Poon, 2005). This feature is important and useful to forecast volatility, suggesting the presence of lag variables of the previous change magnitudes. The frequency of measurement influences the noticeability of clustering. Daily data should normally enable to notice some, however we observe that the trends are even bigger when analysing intra-day data.

ii. Thick tails

Stock and bond returns tend to exhibit fatter tails than normal distribution. These kinds of distribution are called leptokurtic (Mandelbrot, 1963). The degree to which the tails are fatter than a normal distribution can be measured using kurtosis. As stated before, a large value of kurtosis designates a distribution that has fat tails and a sharp peak. Excess kurtosis has two different sources (Bai, et al., 2003). The first one is the volatility clustering, documented above. Indeed, when a large movement occurs, other large movements will follow it, which results in fatter tails of the probability distribution. The second one is the occurrence of non-Gaussian asset returns.

iii. Asymmetry

The well-documented fact that volatility increases more after a negative shock than after a positive one is called the leverage effect (Black, 1976; Nelson, 1991; Bekaert and Wu, 2000). It seems indeed logic that bad news will trigger more reactions from investors than good ones. Thus, after a negative return, we can expect volatility to increase more than after positive ones of the same magnitude (Veronesi, 1999).

b. The different volatility models and their application to stock and bond returns

In order to take the stylized facts documented above into account in the process of estimating the volatility, several models have been developed. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models family is the most widely used. In its simplest expression, a GARCH process enables to reflect the clustering and the time-variability of a time series volatility. Before delving into this subject in details, it should first be mentioned that GARCH models enable to estimate the volatility of the residuals of conditional mean models.

i. Conditional mean models

Autoregressive Moving Average (ARMA) processes enable to estimate the mean of time series given the information set. They can be divided into two different parts. On one hand, the Autoregressive part sets the relation with the previous value of the time series. The Moving Average process gives, on the other hand, the proportionality with the previous innovations of the time series. An ARMA (P, Q) model of conditional mean $\boldsymbol{y_t = E(y_t|\Psi_{t-1}) + \varepsilon_t}$ has the form:

$$\boldsymbol{y_t = \mu + \sum_{i=1}^{P} \phi_i y_{t-i} + \sum_{j=1}^{Q} \varphi_j\, \varepsilon_{t-j} + \varepsilon_t}$$

where $\boldsymbol{\varepsilon_t}$ is the error term, $\boldsymbol{\Psi_{t-1}}$ is the information set at time t-1, $\boldsymbol{\phi}$ and $\boldsymbol{\varphi}$ are parameters.

We can now further study the GARCH processes that model the volatility of the error terms of the conditional mean process.

ii. GARCH processes

A GARCH process (Bollerslev, 1986) is a weighted average of the past conditional variance and the squared error terms. It improves the ARCH model (Engle, 1982) by having a longer memory and a more flexible lag structure. From the ARMA model, we find the error term $\boldsymbol{\varepsilon_t = \sigma_t z_t}$ with $\boldsymbol{z_t \sim iid\ (0, 1)}$ and $\boldsymbol{\sigma_t = E\left(\varepsilon_t^2 \middle| \Psi_{t-1}\right)}$ is changing over time following a GARCH (P, Q):

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-1}^2}$$

where p is the lag order for the autoregression and q is the number of moving average lags with constraints $\boldsymbol{p \geq 0, q > 0, \alpha_0 > 0, \alpha_i \geq 0\ for\ i = 1, \dots, p}$ and $\boldsymbol{\beta_i \geq 0\ for\ i = 1, \dots, q}$ to ensure nonnegativity.

Parameters are estimated using the loglikelihood function. On one hand, large values of $\boldsymbol{\beta}$ indicate that the process is highly impacted by the previous shocks, and exhibits clustering. On the other hand, large values of $\boldsymbol{\alpha}$ show that the process responds quickly and with high magnitude to the previous shocks.
GARCH forecasts are constructed using the values of the parameters estimates. Every forecast is based on the last period and multiple period forecasts are possible. On the long run, the forecasts tend to be equal to the unconditional variance that is equal to:

$$\boldsymbol{\sigma^2 = \frac{\alpha_0}{1 - \sum_{i=1}^{q} \beta_i - \sum_{j=1}^{p} \alpha_j}}$$

if the covariance stationary condition is met: $\boldsymbol{\sum_{i=1}^{q} \beta_i + \sum_{j=1}^{p} \alpha_j < 1}$. The $\boldsymbol{\tau}$-period forecast is found thanks to:

$$\boldsymbol{\widehat{\sigma_{t+\tau}^2} = \frac{\alpha_0}{1 - (\alpha_1 + \beta_1)} + (\alpha_1 + \beta_1)^{\tau}\left(\alpha_1 \varepsilon_t^2 + \beta_1 h_t\right).}$$

Many models have been developed that are based on the GARCH process (Bollerslev, 1986). We will describe the ones that serve the best the purpose of this study, but it is important to note that many others exist. As we can observe in the GARCH model, the asymmetric effect and thick tails documented in the stylized facts are not taken into account. To better reflect these realities of the financial markets, some improvements have appeared.

Asset prices often feature thick tails given the clustering effect. This suggests that the normality assumption used in the GARCH might not be well suited to financial data. That is why Bollerslev (1987) modified his model to be supported by t-distributed data. It leads to more accurate estimations of the volatility of financial assets. With the innovation process $\boldsymbol{\varepsilon_t = \sigma_t z_t}$, we have $\boldsymbol{z_t = \sqrt{\frac{\nu-2}{\nu}} T_\nu}$ with $\boldsymbol{\nu}$ the degrees of freedom and $\boldsymbol{T_\nu}$ follows a Student's t distribution.

The leverage effect on volatility documented above is reflected in the asymmetric GARCH models. In particular, the GJR-GARCH developed by Glosten, Jagannathan and Runkle (1993) allow their modelled volatility to respond differently depending on whether the previous shock was positive or negative by introducing a dummy variable as follows:

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 + \sum_{p=1}^{P} \alpha_p \varepsilon_{t-p}^2 + \sum_{r=1}^{R} \gamma_r D_{r,t-1} \varepsilon_{t-r}^2}$$

$$\boldsymbol{D_{t-1} = \begin{cases} 1, & and \varepsilon_{t-1} < 0 \\ 0, & and \varepsilon_{t-1} \geq 0 \end{cases}}$$

if the $\boldsymbol{\gamma}$ are estimated >0, it gives evidence that negative shocks have a higher impact on volatility than positive ones.

The $\boldsymbol{\tau}$-period forecast is given by the following (Poon, 2005):

$$\boldsymbol{\widehat{\sigma_{t+\tau}^2} = \alpha_0 + \left(\frac{1}{2}(\alpha_1 + \gamma_1) + \beta_1\right) \sigma_{t+\tau-1}^2}$$

Another asymmetric volatility model is the Threshold GARCH (TARCH) of Zakoian (1994). The main difference with GJR-GARCH is that this process responds to the absolute values of innovations rather than their square value:

$$\boldsymbol{\sigma_t = \alpha_0 + \sum_{p=1}^{P} \alpha_p |\varepsilon_{t-p}| + \sum_{r=1}^{R} \gamma_r D_{r,t-r} |\varepsilon_{t-r}| + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}}$$

c. Evaluation of the suitability of a model

The difficulty of applying econometrical frameworks holds often to the fit of data to the model used. The whole empirical research has been realized with Matlab (2014a version). While this programming software is not the most elaborated in statistics and econometrics, compared to R, it has improved impressively lately in those areas and presented all the functions needed to apply the ADCC model. Furthermore, it is the software for which we have the most experience with and thus practical knowledge.

Here below, we will conduct the first stage of the Asymmetric Dynamic Conditional Correlation model of Engle (2004), which consists in the fitting of the volatility models of the asset returns series. Two possibilities in order to estimate the ADCC model using Matlab. One can either program every step by oneself, or can either employ the MFE toolbox developed and made available by Kevin Sheppard (2009). The advantage of this toolbox is the possibility to fit TARCH models to univariate asset returns series, which is not available in the standard functions of the econometric toolbox of Matlab. Furthermore, the toolbox optimizes the variance-targeting step, which is otherwise very complex to perform. Unfortunately, using this toolbox doesn’t allow as much flexibility as one would have by developing every step by oneself since it does not permit to use different volatility processes for the univariate series. After having tried the first method and having encountered major difficulties in estimating ARMA models and the variance-targeting equation, we decided to use the second one. As we couldn’t fit the data to an ARMA model, we simply define the residuals as the demeaned returns, as suggested by Christoffersen and Diebold (2006).

i. Pre-estimation analysis

First, it is necessary to test whether the returns series are stationary, i.e. the expected value and autocovariance of the time series are independent of time. Computing the returns leads to a higher chance of stationarity, compared to working with the raw price series. Hence, we need to test the returns series of stocks and bonds in Europe and in the United States. The augmented Dickey-Fuller tests for the presence of a unit root in a univariate time series, the intuition behind this test being that if there is no unit root, the time series will be stationary.

We fit the time series to the following relation:

$$\boldsymbol{y_t = c + \delta t + \phi y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t}$$

with the null hypothesis H0: $\boldsymbol{\phi = 1}$.

We observe that the null hypothesis is rejected for the four asset returns series, suggesting that they are all stationary.
Then, the normality of the centred returns has to be tested. However, as we can see in the plotted data, extreme values seem to be too deviant from the normality distribution. This is confirmed by Jarque-Bera tests whose formula is:

$$\boldsymbol{JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)}$$

with S the skewness and K the kurtosis, documented previously.

The tests statistics all reject the null hypothesis of normality with a p-value less than 0,0001. While this may seem to be an issue for the rest of our analysis, it is essential to note that the ADCC model is applied on the standardized returns that, as Cappiello et al. (2006) have proved it, almost always follow a normal distribution.

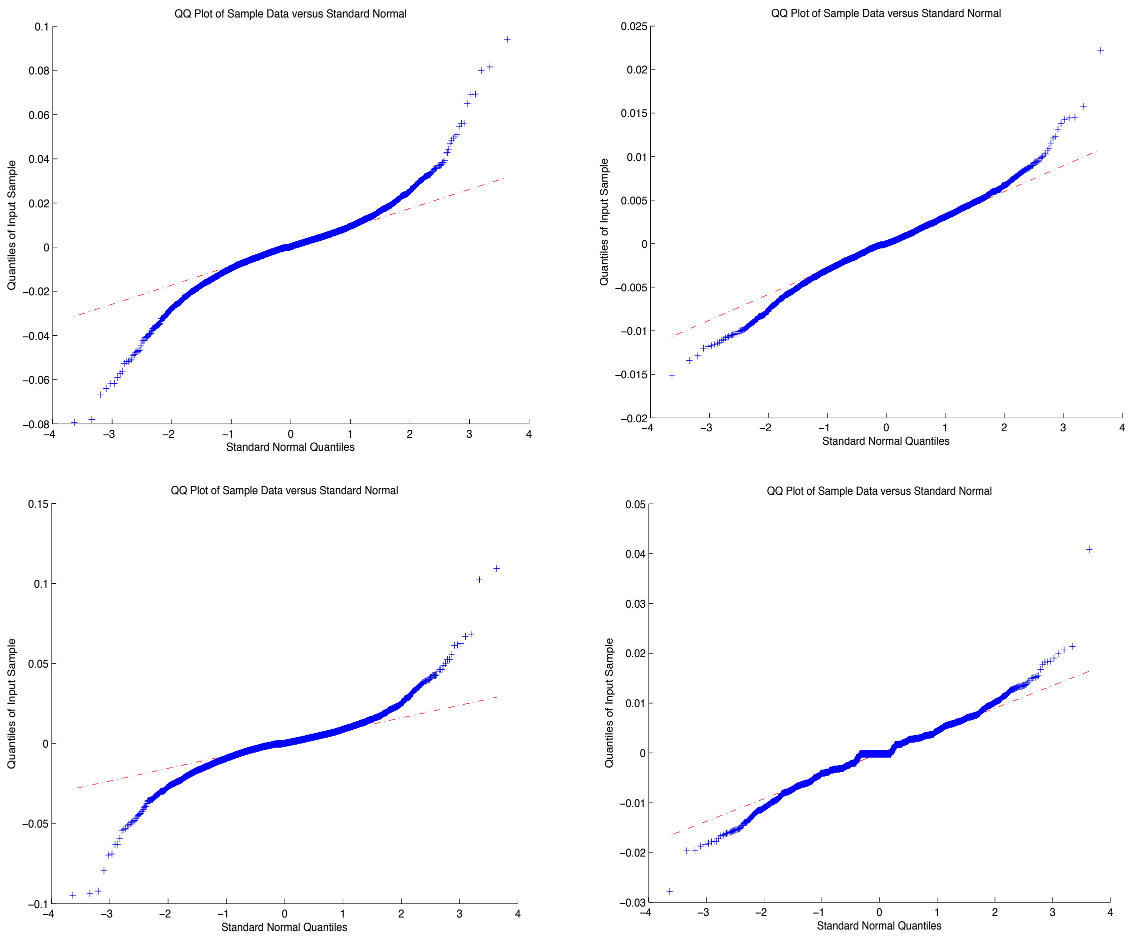

Figure 3.1 QQ-plots of the centred returns compared to a Normal distribution

The next step is to test for serial correlation among the centred returns, this test provides a good insight of whether the time series features clustering or not. The statistics used is the Ljung-Box Q-test that tests the null hypothesis of no autocorrelation given by the formula:

$$\boldsymbol{Q = T(T+2)\sum_{k=1}^{L}\left(\frac{\rho(k)^2}{(T-k)}\right)}$$

with T the sample size, L the number of lags and $\boldsymbol{\rho(k)^2}$ the sample autocorrelation at lag k.

In this case, the four time series reject the null hypothesis with p-values lower than 0,0001.

The last test we apply during the pre-estimation analysis is the Engle's ARCH test. It enables to verify whether the asset returns series are homoscedastic. If it were the case, a GARCH model would not represent a valuable option since it is used to model heteroskedastic time series. The null hypothesis is again clearly rejected for each return series.

ii. Choice of the framework

After the pre-estimation analysis, it is now time to fit the asset returns series to univariate GARCH models. As well documented previously, the best fit should be asymmetric volatility models. However, we decide to make estimations for the classical symmetric models also. The decision rule in this case is the Akaike Information Criterion (AIC). This criterion enables to choose the best number of different lags as well as the kind of volatility model that fits best the data. It is based on the maximum likelihood function, and conversely to BIC but taking this decision criterion does not lead to data overfitting. Indeed, the AIC takes the number of parameters in the model into account and gives a balance between the fitting and the number of parameters. As suggested by Burnham and Anderson (2002), we decide to pick AIC instead of BIC as it gives lower penalty for the number of parameters. Here is the formula:

$$\boldsymbol{AIC = T\, ln(sum\ of\ squared\ residuals) + 2}$$

with T the number of parameters in the model.

To the extent that we wish to obtain low residuals with few parameters, we will pick the model with the lowest AIC.
The decision tree will then be the following: we first eliminate the models whose any parameter is not statistically significant at the 5% confidence level. Afterwards, among the remaining processes, we pick the one with the lowest AIC value.

iii. Results of the suitability of the univariate GARCH processes

Emphasis is first placed on the European stock and bond markets. As the MFE Toolbox (Sheppard, 2009) does not enable to pick different GARCH process for the volatility models, we need to pick the one that fits best both assets markets. This represents certainly a drawback since it might have been preferable to pick different models for the stock and bond markets. However, the loss of information isn't too important as revealed by the results that we find below:

	w	a1	a2	g1	g2	b1	b2	AIC
TARCH(1,0,1)	0.00025702	0.10717	0,00	0,00	0,00	0.89263	0,00	-22833,00
	0.00013407	0,00	0,00	0,00	0,00	0,00	0,00	
TARCH(1,1,1)	0.00021971	0,01	0,00	0.14049	0,00	0.92504	0,00	-23068,00
	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
TARCH(1,1,2)	0.00022295	0,17	0,00	0.14283	0,00	0.90584	0.017981	-23068,00
	0,00	0,00	0,00	0,00	0,00	0,00	0,00	
TARCH(2,1,1)	0.00021969	0,00	0,00	0.14047	0,00	0.92504	0,00	-23068,00
	0,00	0.7141	0,00	0,00	0,00	0,00	0,00	
TARCH(1,2,1)	0.00021972	0,00	0,00	0.14049	0,00	0.92504	0,00	-23068,00
	0,00	0,00	0,00	0,00	0,64	0,00	0,00	
GARCH(1,1)	0,02	0.10125	0,00	0,00	0,00	0.88833	0,00	-22847,00
	0,50	0,00	0,00	0,00	0,00	0,00	0,00	
GJR-GARCH(1,1,1)	0,02	0,00	0,00	0.16809	0,00	0.90053	0,00	-23040,00
	0,00	0.0083204	0,00	0,00	0,00	0,00	0,00	
GJR-GARCH(1,1,2)	0,02	0,00	0,00	0.1679	0,00	0.90047	0.00017122	-23040,00
	0,00	0.94704	0,00	0,00	0,00	0,00	0,00	
GJR-GARCH(2,1,1)	0,02	0,00	0,00	0.1681	0,00	0.90053	0,00	-23040,00
	0,00	0.67971	0,00	0,00	0,00	0,00	0,00	
GJR-GARCH(1,2,1)	0,02	0,00	0,00	0.16808	0,00	0.90053	0,00	-23040,00
	0,01	0.0073093	0,00	0,00	0,02	0,00	0,00	

Table 3.1 Volatility models for EU equities

	w	a1	a2	g1	g2	b1	b2	AIC
TARCH(1,0,1)	0,29	0.037949	0,00	0,00	0,00	0.96185	0,00	-31178,00
	0.0098033	0,00	0,00	0,00	0,00	0,00	0,00	
TARCH(1,1,1)	0,25	0.042464	0,00	-0.020207	0,00	0.96744	0,00	-31190,00
	0.020059	0,00	0,00	0.0031888	0,00	0,00	0,00	
TARCH(1,1,2)	0,39	0.065667	0,00	-0.031381	0,00	0.38055	0.56927	-31191,00
	0.0055081	0,00	0,00	0.014186	0,00	0.070348	0.0058763	
TARCH(2,1,1)	0,25	0.042462	0,02	-0.020207	0,00	0.96744	0,00	-31190,00
	0.0063778	0,00	0.020587	0.0025834	0,00	0,00	0,00	
TARCH(1,2,1)	0,25	0.042465	0,00	-0.020206	0,00	0.96744	0,00	-31190,00
	0.0043857	0,00	0,00	0.0056324	0.10487	0,00	0,00	
GARCH(1,1)	0,00	0.034609	0,00	0,00	0,00	0.95719	0,00	-31188,00
	0.0056353	0,00	0,00	0,00	0,00	0,00	0,00	
GJR-GARCH(1,1,1)	0,00	0.042471	0,00	-0.021277	0,00	0.96144	0,00	-31197,00
	0.0035424	0,00	0,00	0.01412	0,00	0,00	0,00	
GJR-GARCH(1,1,2)	0,00	0.057215	0,00	-0.028474	0,00	0.58563	0.36216	-31198,00
	0.89203	0.85615	0,00	0.84583	0,00	0.93905	0.96068	
GJR-GARCH(2,1,1)	0,00	0.042478	0,02	-0.021284	0,00	0.96143	0,00	-31197,00
	0.032811	0,01	0.087054	0.013813	0,00	0,00	0,00	
GJR-GARCH(1,2,1)	0,00	0.042471	0,00	-0.021277	0,00	0.96144	0,00	-31197,00
	0.0039999	0,01	0,00	0.0066137	0.35002	0,00	0,00	

Table 3.2 Volatility models for EU bonds

The tables contain the value of the parameters for each process with the corresponding p-values below when applicable, and eventually the AIC.

We notice that few processes manage to be statistically significant on all their parameters in both stock and bond markets. Among them, the TARCH (1,1,1) is the one who presents the lowest AIC value, and hence is the one to be picked for the following steps. It presents the lowest AIC in the stock market and a very low loss of information in the bond market compared to the GJR-GARCH (1,1,1).

The following tables are the results for the United States, respectively relating to the equities and bond markets:

	w	a1	a2	g1	g2	b1	b2	AIC
TARCH(1,0,1)	0,0002	0,0849	0,0000	0,0000	0,0000	0,9149	0,0000	-23078,0000
	0,0010	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	
TARCH(1,1,1)	0,0002	0,0009	0,0000	0,1353	0,0000	0,9296	0,0000	-23297,0000
	0,0007	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	
TARCH(1,1,2)	0,0002	0,0000	0,0000	0,1364	0,0000	0,9316	0,1255	-23296,0000
	0,0009	0,9998	0,0000	0,0000	0,0000	0,0000	0,0000	
TARCH(2,1,1)	0,0002	0,0256	0,0002	0,1351	0,0000	0,9295	0,0000	-23297,0000
	0,0017	0,1209	0,1061	0,0000	0,0000	0,0000	0,0000	
TARCH(1,2,1)	0,0002	0,0000	0,0000	0,1353	0,0001	0,9296	0,0000	-23297,0000
	0,0007	0,0032	0,0000	0,0000	0,0000	0,0000	0,0000	
GARCH(1,1)	0,0145	0,0825	0,0000	0,0000	0,0000	0,9058	0,0000	-23130,0000
	0,0007	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	
GJR-GARCH(1,1,1)	0,0154	0,0000	0,0000	0,1399	0,0000	0,9146	0,0000	-23293,0000
	0,2107	0,7104	0,0000	0,0000	0,0000	0,0000	0,0000	
GJR-GARCH(1,1,2)	0,0154	0,0000	0,0000	0,1399	0,0000	0,9146	0,0211	-23293,0000
	0,4765	0,9967	0,0000	0,0000	0,0000	0,0000	0,9000	
GJR-GARCH(2,1,1)	0,0154	0,0000	0,0023	0,1399	0,0000	0,9146	0,0000	-23293,0000
	0,4545	0,4708	0,0000	0,0000	0,0000	0,0000	0,0000	
GJR-GARCH(1,2,1)	0,0154	0,0001	0,0000	0,1399	0,0001	0,9146	0,0000	-23293,0000
	0,2965	0,0006	0,0000	0,0000	0,0007	0,0000	0,0000	

Table 3.3 Volatility models for US equities

	w	a1	a2	g1	g2	b1	b2	AIC
TARCH(1,0,1)	0,4284	0,0375	0,0000	0,0000	0,0000	0,9623	0,0000	-28400,0000
	0,0467	0,0001	0,0000	0,0000	0,0000	0,0000	0,0000	
TARCH(1,1,1)	0,0000	0,0414	0,0000	-0,0138	0,0000	0,9653	0,0000	-28405,0000
	0,2191	0,0011	0,0000	0,2684	0,0000	0,0000	0,0000	
TARCH(1,1,2)	0,3921	0,0414	0,0000	-0,0138	0,0000	0,9653	0,4954	-28405,0000
	0,1214	0,0003	0,0000	0,0683	0,0000	0,0000	0,3051	
TARCH(2,1,1)	0,4104	0,0270	0,0158	-0,0134	0,0000	0,9637	0,0000	-28406,0000
	0,5953	0,2327	0,7314	0,2002	0,0000	0,0000	0,0000	
TARCH(1,2,1)	0,3921	0,0414	0,0000	-0,0138	0,0001	0,9653	0,0000	-28405,0000
	0,2700	0,3170	0,0000	0,0974	0,0000	0,0000	0,0000	
GARCH(1,1)	0,0010	0,0333	0,0000	0,0000	0,0000	0,9627	0,0000	-28430,0000
	0,0250	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	
GJR-GARCH(1,1,1)	0,0009	0,0404	0,0000	-0,0160	0,0000	0,9640	0,0000	-28436,0000
	0,0095	0,0004	0,0000	0,0484	0,0000	0,0000	0,0000	
GJR-GARCH(1,1,2)	0,0009	0,0405	0,0000	-0,0160	0,0000	0,9630	0,0010	-28436,0000
	0,0764	0,0000	0,0000	0,0286	0,0000	0,0000	0,1390	
GJR-GARCH(2,1,1)	0,0010	0,0290	0,0123	-0,0158	0,0000	0,9629	0,0000	-28436,0000
	0,0847	0,0174	0,3754	0,0679	0,0000	0,0000	0,0000	
GJR-GARCH(1,2,1)	0,0001	0,0404	0,0000	-0,0160	0,0001	0,9640	0,0000	-28436,0000
	0,0616	0,0000	0,0000	0,5374	0,6632	0,0000	0,0000	

Table 3.4 Volatility models for US bonds

Again, there are very few processes with significant parameters in both univariate series. In this case, we experience some larger loss of information and finally pick the GARCH (1,1) process. Surprisingly enough, it is not even an asymmetric process. Other volatility models show better AIC values but are unfortunately not significant in both markets.

We test the serial autocorrelation of the residuals and obtain the following p-values:

P-value	EU	US
Stocks	0,9247	0,9347
Bonds	0,3252	0,0615

Table 3.5 Ljung-Box Q-test of residuals

We fail to reject the null hypothesis of no autocorrelation, demonstrating that the processes are good fits.

Subsequently, the Engle's ARCH test is applied in order to test whether the standardized residuals feature remaining ARCH effect. It basically tests the proportionality with the lagged residuals implying that if some remains, the number of coefficients linked to lagged residuals should be modified. The tests estimated the parameters of the following formula defining the residuals:

$$\boldsymbol{r_t^2 = a_0 + a_1 r_{t-1}^2 + \cdots + a_L r_{t-L}^2 + e_t}$$

The test statistics is $\boldsymbol{TR^2}$ with T the sample size and follows a Xhi-squared distribution, and the null hypothesis H0: $\boldsymbol{a_0 = a_1 = \cdots = a_L}$. Here are the results:

P-value	EU	US
Stocks	0,9148	0,7934
Bonds	0,8767	0,5438

Table 3.6 ARCH test of residuals

The null hypothesis is hopefully kept in every case, suggesting there is no ARCH effect remaining in the residuals.

Those two tests suggest that the picked GARCH processes fit accurately the univariate time series.

d. The correlation model

After having fitted the univariate series volatility, we can now consider the second step of the ADCC model. It consists of the different variance targeting equations, and the easy computation of the correlation coefficient coming from the conditional covariances. For an easier use, here is a recall of the second step documented previously:

$$Q_t = (1 - \alpha - \beta - \gamma) * \bar{Q} + \alpha\, z_{t-1}z'_{t-1} + \beta Q_{t-1} + \gamma \lambda_{t-1}\lambda_{t-1}{}'$$
$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}$$

The following results are obtained for the European markets:

Parameters	Correlation	alpha	beta	gamma	Likelihood
Values	-0,4049	0,0418	0,0094	0,9376	27557,188

Table 3.7 Parameters of the EU ADCC model

The asymmetry of the second moments is clearly noticeable with a stronger reaction to negative shocks than positive ones. A very low average correlation is observed in the European market.

In the United States, the following parameters are collected:

Parameters	Correlation	alpha	beta	gamma	Likelihood
Values	-0,3318	0,0343	0,0106	0,9514	26099,444

Table 3.8 Parameters of the US ADCC model

Again, the reaction to negative second moments is largely more important than the one to positive second moments. If the average correlation observed is a bit higher than in Europe, it remains quite low.
On a time-varying framework, we achieve the following charts, which we compare with a 22-day rolling correlation, respectively for the European and the United States market:

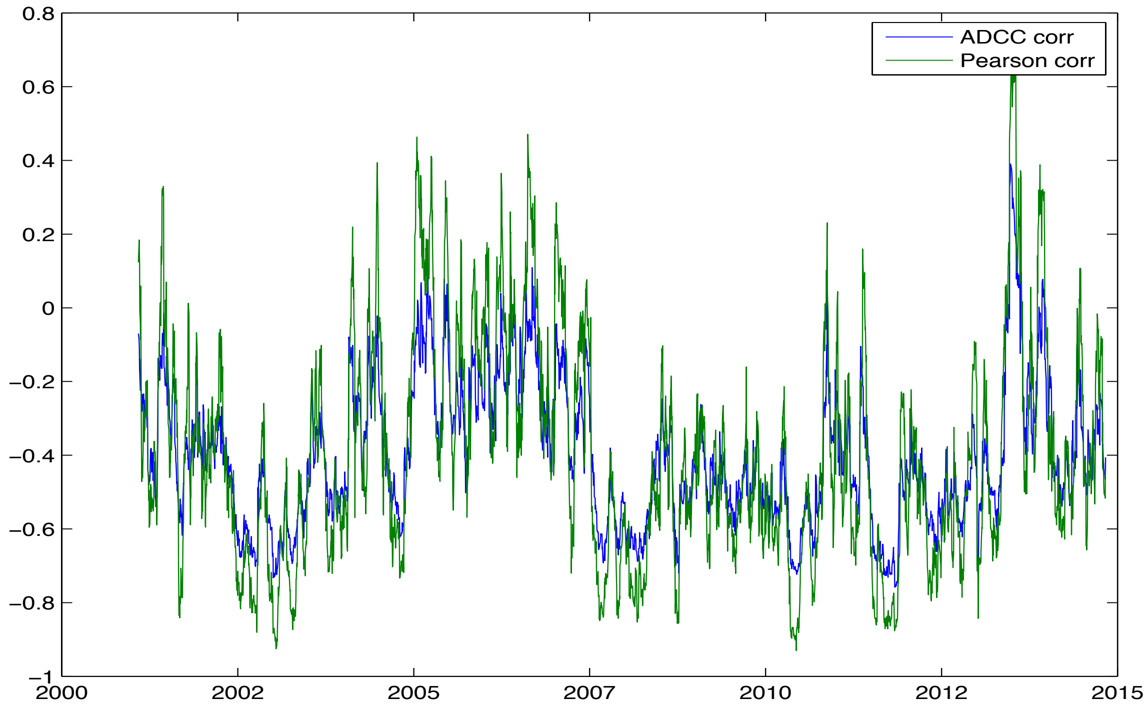

Figure 3.1 Comparison of ADCC and Pearson correlation in EU

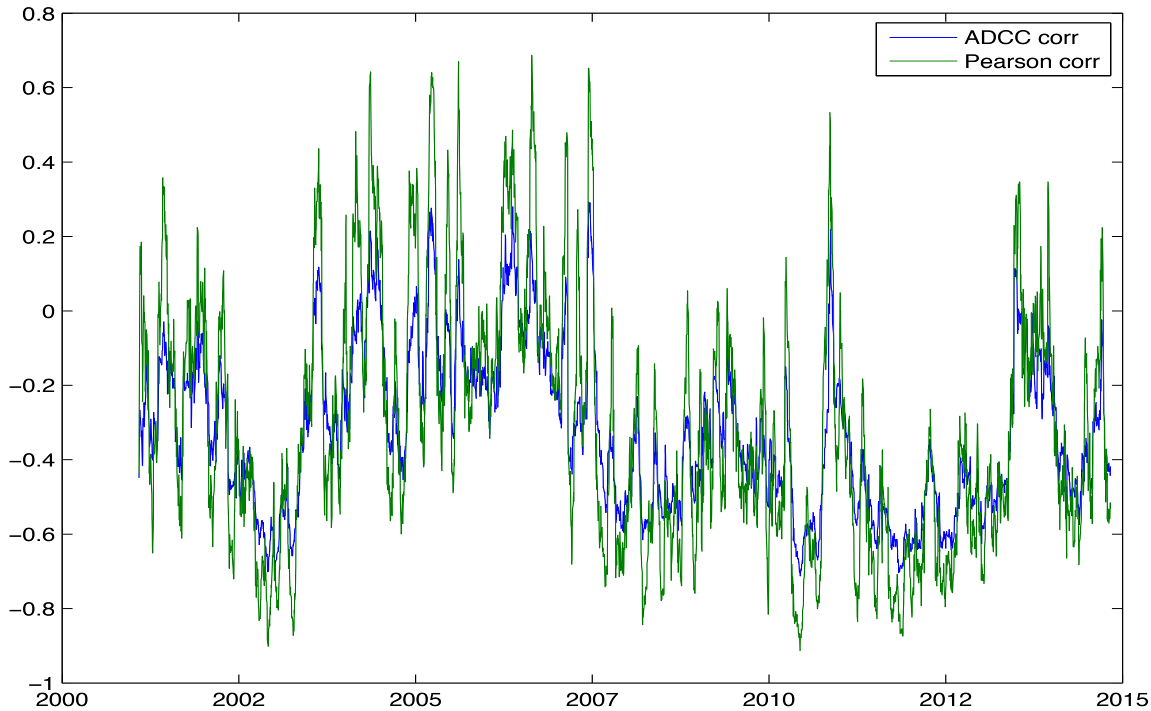

Figure 3.2 Comparison of ADCC and Pearson correlation in the US

The Pearson coefficient correlation noticeably exhibits a more volatile pattern than the ADCC correlation, as expected, due to values getting in and out of the rolling window. The general trends however are really similar on average. A deeper analysis of the present values will be processed in the next section.

4. Analysis of the correlation during crises

To analyse how the correlation coefficient has evolved during the different economic conditions since 2001, we base our work on the ADCC model because of its conceptual strengths documented above. Furthermore, to prevent our analysis from being biased by short-term disturbances, we conduct our analysis on an average of 22 days of the Asymmetric Dynamic Conditional Correlation.

However, when simply computing the arithmetic mean of correlation, we observe that the coefficient is underestimated in absolute value (Gorsuch and Lehmann, 2010). Plus, the standard error of the arithmetic mean of correlations also biased because of the skewness of the distribution, resulting in inequalities between below and above the mean deviations (Fisher, 1921). Gorsuch and Lehmann (2010) show that z transformations adequately respond to those two issues and highly improve the quality of means of correlation coefficients even for large samples. The z transformation was developed by Fisher to normalize the distribution of the coefficients, and hence to improve the computation of their mean and standard deviation. We apply the following formulas to the correlations coefficients $\boldsymbol{\rho}$:

$$\boldsymbol{z = O,5 * (log(1+\rho) - log(1-\rho))}$$

Then we compute the arithmetic means of the z. Afterwards, in order to come back to average correlation coefficients, we apply:

$$\boldsymbol{\rho = (exp(2*z) - 1)/(exp(2*z) + 1)}$$

Those small transformations enable to deal with unbiased data. Here below are the resulting charts in the European market:

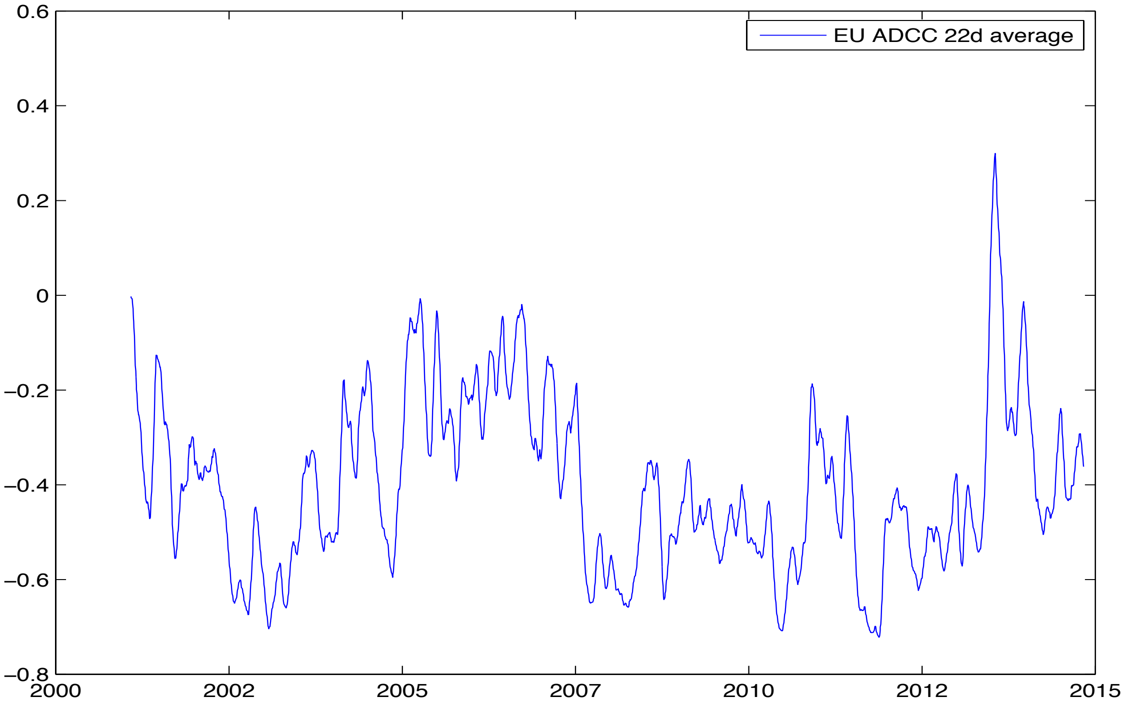

Figure 4.1 EU 22-day ADCC average

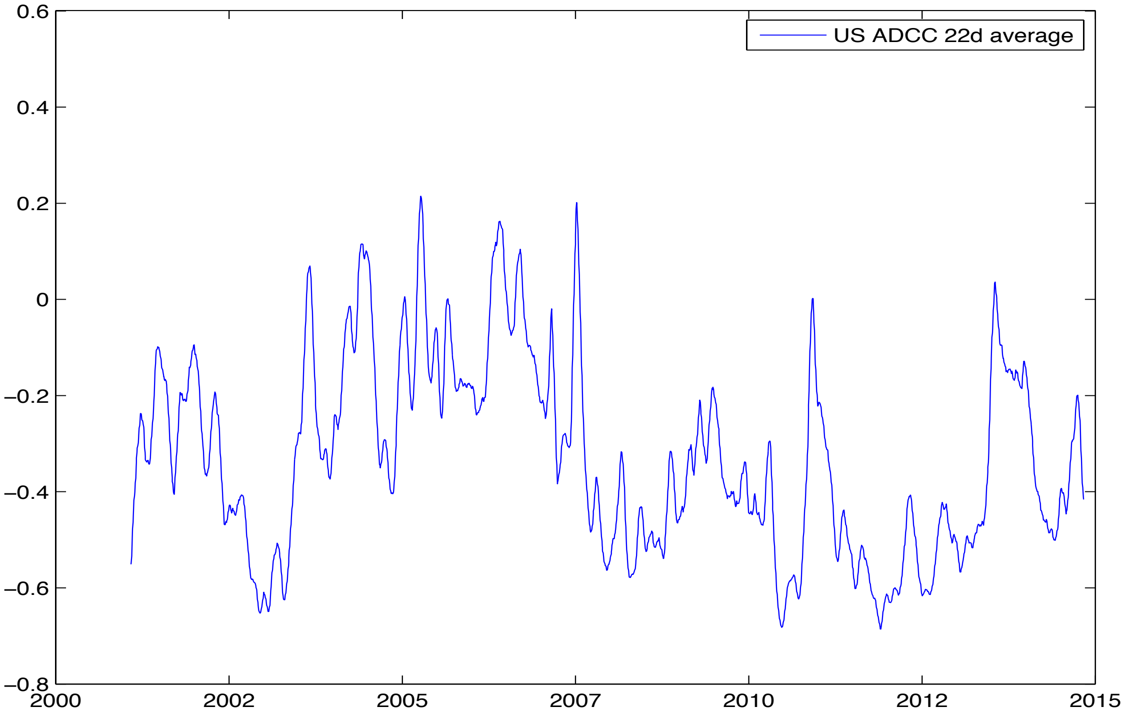

Figure 4.2 US 22-day ADCC average

The average correlation in the European and the United States markets from February 2001 to October 2015 are respectively of -0,41 and -0,33, which are very low values compared to previous periods and are consistent with studies of contemporaneous times (Chiang and Li, 2009; Ilmanen, 2003). Those values are similar to the ones found during the crash state documented by Guidolin and Timmermann (2006). Negative, those results suggest the occurrence of flights between assets given the episodes of financial turmoil since the beginning of the 21st century.

We will further analyse the value of the stock-bond correlation during the 2007-2009 global financial crisis and the Euro area sovereign debt crisis[2]. To this end, and since financial markets are subject to many distinct influences, making point-by-point analysis difficult, our investigation will be based on an overall picture.

a. Stock-bond correlation during the 2007-2009 global financial crisis

The referenced starting point of the subprime crisis is given in the end of July 2007 (Kenourgios, Christopoulos and Dimitriou, 2013). And we will analyse the evolution of the stock-bond correlation till the end of the recession in June 2009 as indicated by the National Bureau of Economic Research.

[2] It is important to point out that the goal of this chapter is to analyse the movements of stock-bond correlation but under no instances, to provide a detailed timeline and causes of he two crises. For further information about the development and causes of the crises, we recommend the studies of Eichengreen et al. (2011) and Lane (2012). Recent news about the Euro debt crisis have been collected on www.Bloomberg.com.

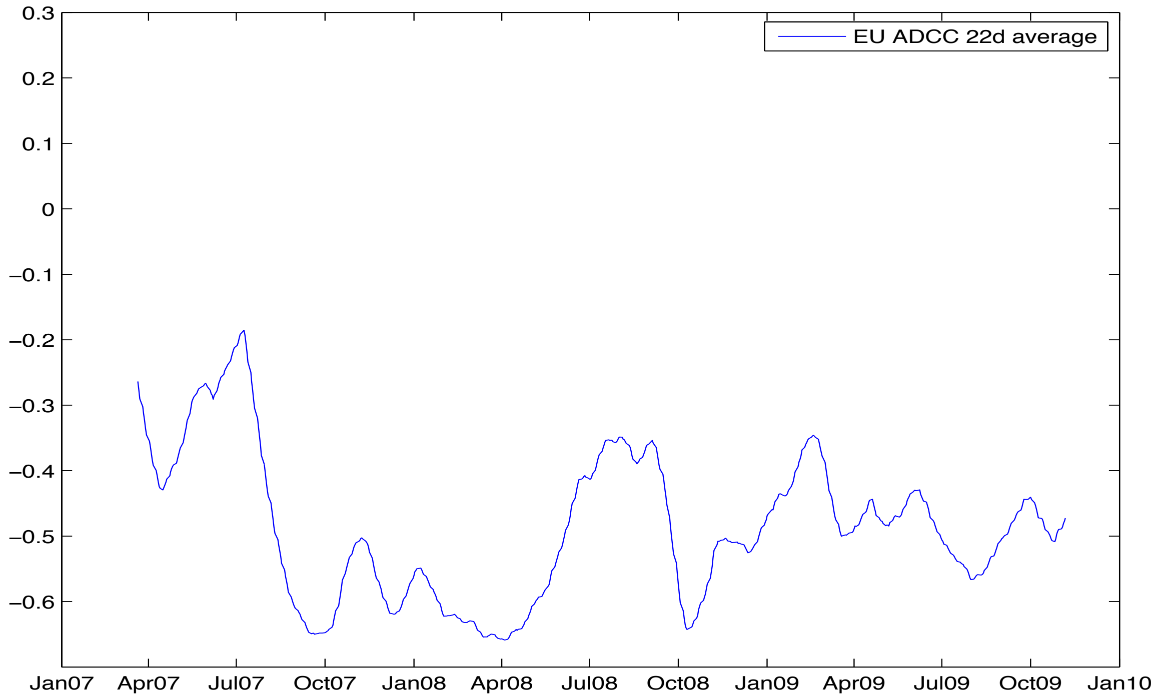

Figure 4.3 EU 22-day average ADCC Jan07-Jan10

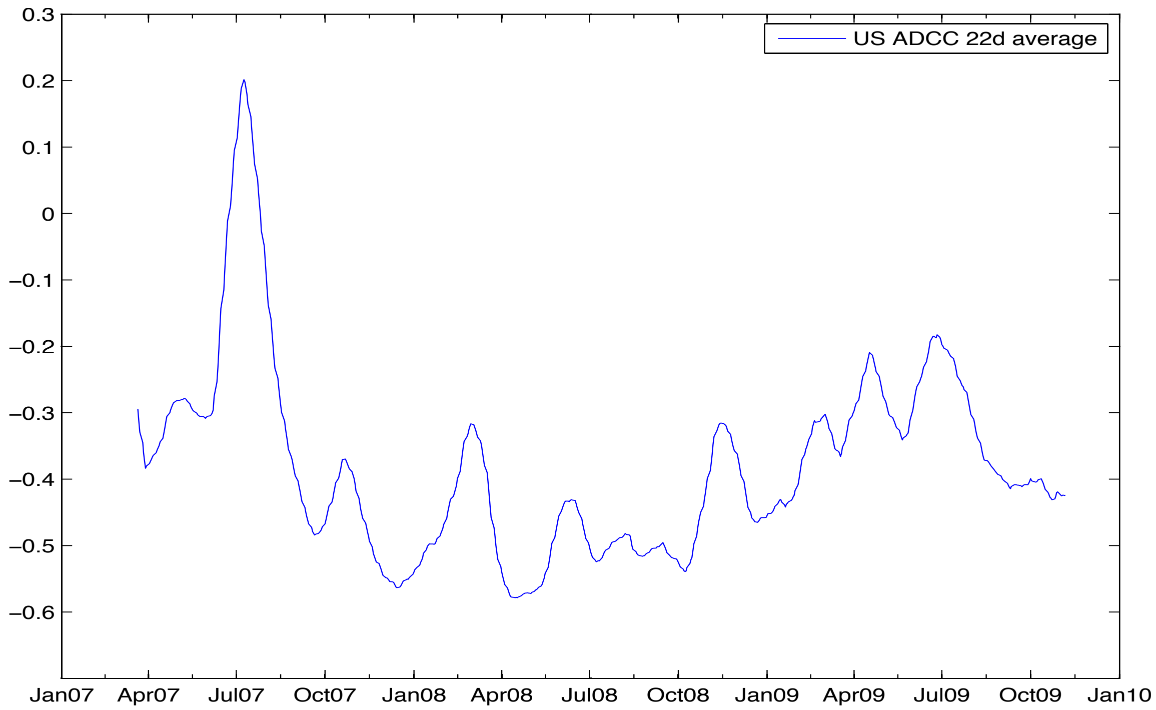

Figure 4.4 US 22-day average ADCC Jan07-Jan10

In July 2007, banks began to depreciate the value of their assets linked to subprime mortgages. This devaluation led to a massive drop in stock prices. In the charts, we indeed observe that the stock-bond correlation impressively fell after July 2007 till the end of September 2007 both in Europe and the United States. Stockholders feared for their investments and started disinvesting in equities. As government bonds are a safer investment option than stocks and given the financial situation, they appeared attractive to investors who massively moved their stakes towards them. This shift resulted in the bond markets rising sharply. Falling equities and climbing government bonds led to the plunge of stock-bond correlations. A large Flight-To-Quality happened. As we notice, the coefficient remains low during the rest of the 2007-2009 global financial crisis.

The impressive drop in stock markets following the bankruptcy of Lehman Brothers and fears of AIG's insolvency in September 2008 is clearly reflected in the European stock-bond correlation as it falls deeper after the small regain, suggesting the resumption of the Flight-To-Quality after a small surge of the coefficient.

In October 2008, a rally of stock-bond correlation was noticed in Europe and the United States as a consequence of the lowering of rates by diverse central banks, the relaxing of rules for United States companies repatriating money from subsidiaries abroad as well as the provision of $900 billion in cash loans by the FED. Those governmental measures led to end the panic in financial markets. However, we observe that the coefficient remains low during the rest of the crisis, reflecting the lack of confidence that investors had in the economy at that time.

b. Stock-bond correlation during the Euro area sovereign debt crisis

In October 2009, Greece's government released modified figures of the debt situation of the country. The revised forecasts indicate that Greece's budget deficit is four times higher than the EU limit. This episode can be considered as the start of the Euro area sovereign debt crisis.

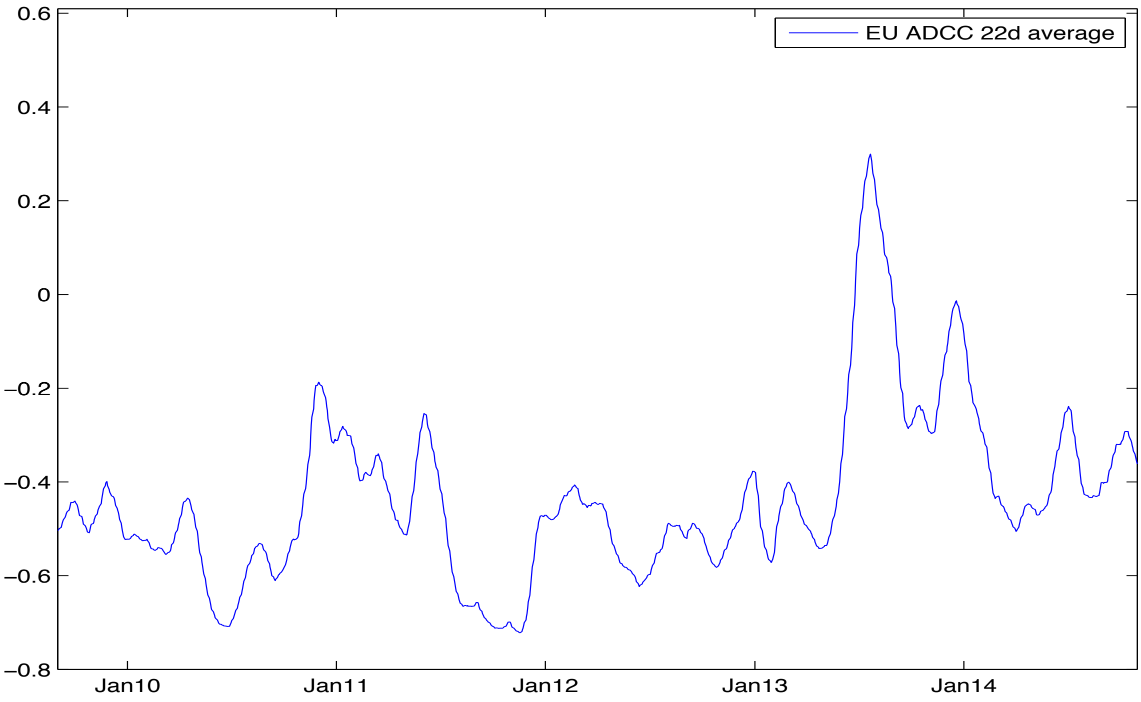

Figure 4.5 EU 22-day average ADCC Oct09-Oct14

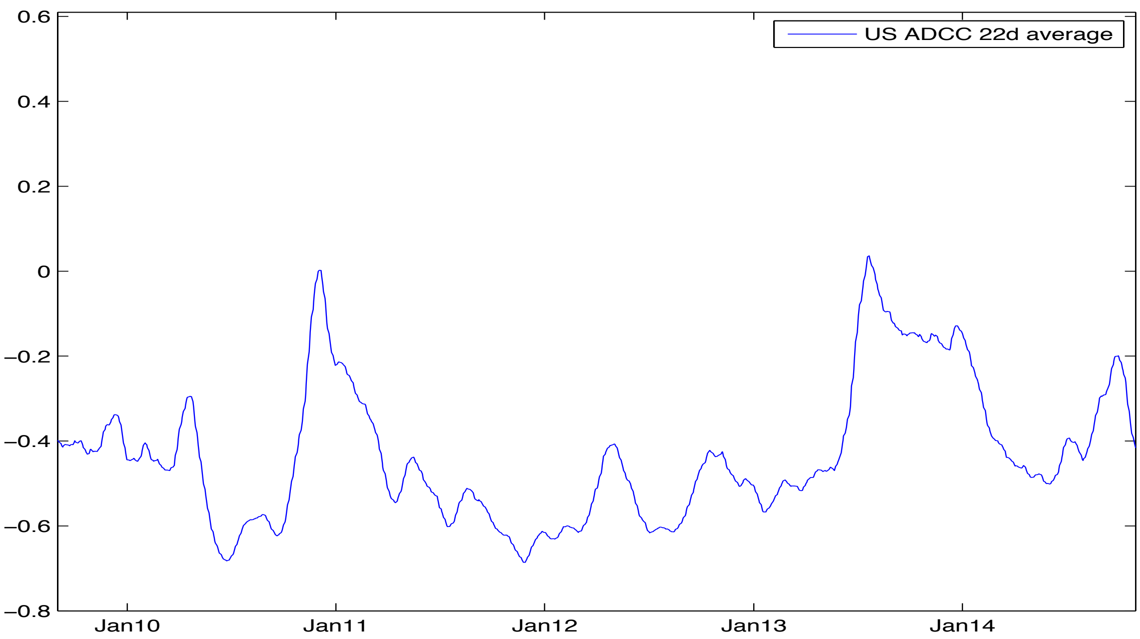

Figure 4.5 EU 22-day average ADCC Oct09-Oct14

This already led to higher borrowing costs for the country and despite the adoption of an austerity plan in early 2010, Greece was granted a 30€ billion loan by the Euro area finance ministers and 15€ billion in funds by the IMF in order to avoid a default.

After a first bailout of 110€ billion to rescue Greece, other EU member states got under the scrutiny of financial investors. Hence, Euro area government bonds globally suffered from the spillover effect from Greece and from an aggregate regional risk factor (De Santis, 2012), resulting in bear bond market starting in the second half of 2010. In response, the stock-bond correlation in Europe got surprisingly low due to a rising stock market and declining bonds. With the situation of government bonds, those assets were not considered as safe anymore. Besides, in case of financial turmoil, investors are necessarily looking for safe and liquid opportunities that enable them to promptly get their money back from their assets in case of worsened financial conditions. That is why at that point of time, investors were flowing away from the government bonds. It can actually be perceived as a Flight-From-Quality, which normally appears in bright economic conditions as investors regain confidence and decide to assume more risks. However, given the darkened financial outlook at that time, it seems more likely that a Flight-To-Liquidity has happened, which is defined as a flight to the more liquid asset (Baur and Lucey, 2006), namely in Europe the German Bund (De Santis, 2013). However, given that most of other bonds had been declining, equities presented the advantage to be more liquid than high-yield government bonds within this period. Later, stock-bond correlations rally as bond markets were slowing their decline. The same situation was also observed in the United States where bonds probably suffered from the spillover effect of the debt crisis in Europe.

In August 2011, we notice a clear decoupling episode with declining stocks and rising treasury bonds. After the downgrading of America’s credit rating from AAA to AA+ by S&P, stock markets fell sharply. Further decreases followed amid concerns about the credit rating of France and contagion of the sovereign debt crisis to Spain and Italy. In this case, it appears that a Flight-To-Quality happened as investors have been flying away from stocks to invest in bonds.

Further in 2011 and 2012, investors’ confidence seemed to remain low. This sentiment can probably be explained by various countries credit ratings downgraded, new Greek bailouts and debt write-off, high borrowing costs for unstable countries as well as fears of a Greece default.

In June 2013, some strong bear movements in bonds and stock markets were observed in Europe and the United States. Those negative changes were the consequence of declarations made by Ben Bernanke. Indeed, he explicitly stated that the FED might start tapering its bond buying later in the year, leading to a rise in investors fear. Stock markets fell sharply, so did the bond market anticipating the possible impact of an increase in interest rate on bond prices. Consequently, stock-bond correlation experienced an impressive climb. In this case, as the coefficient rose to positive values, diversification opportunities got scarcer between equities and government bonds. The premises of a possible contagion appeared. Hopefully, the coefficient quickly came back to usual levels and no further observations can be applied to the recent developments of the Euro area sovereign debt crisis.

In summary, Flights-To-Quality, Flight-To-Liquidity and a contagion episodes have been observed during the sovereign debt crisis. It might be judicious to continue to analyse the evolution of the stock-bond correlation and its resulting consequences as his examination always provides valuable information about investors sentiment and diversification possibilities.

5. Explaining the stock-bond correlation

a. Listing of the explaining factors

i. Explaining factors encountered in the literature

Given the low value of the stock-bond correlation since the beginning of the 21st century, an analysis of its sensitivity to its usual drivers is undertaken in order to determine whether explanations can be found.

To ease the understanding of the reader, we quickly enumerate the different drivers and the sign of their regression coefficients previously found in the literature. Among macroeconomic variables, expected inflation and interest rates impact positively the stock-bond return comovements and a similar relation is found between liquidity and SBC in the literature. In previous studies, mixed results about the link between economic growth and stock-bond correlation were demonstrated. On the contrary, measures of uncertainty about different economic variables systematically feature a negative relation with the stock-bond return relation.

ii. Explaining factors used in this study

The list of explaining factors used in this study differs slightly from the one of the previous literature given their easiness of availability. Indeed, we study the relation between the stock-bond correlation and inflation (INF), expected inflation (EXPINF), GDP growth (GDP), implied volatility of equity options indexes (VOL) and interest rates (INT).

Regrettably, it has not been possible to find a satisfying proxy of the liquidity in Europe and in the United States. And for the uncertainty measure, we decide to pick the implied volatility of equity options indexes on the grounds of its experimental advantages highlighted by Connolly, Stivers and Sun (2005). We study the relation on a monthly basis, taking the 15th of each month as the reference date. However, due to the fact that some data are only available on a quarterly basis (GDP and expected inflation) and that another time series is given at the end of each month, we develop the technique of cubic spline interpolation in order to overcome those issues and get values on the 15th of each month for all time series.

As shown by Ajao, Ibraheem and Ayoola (2012), the use of this technique gives robust results and is not overly complex to develop. It produces missing data efficiently even for highly diversified datasets. The first step of the method is the development of third order curves for each interval between existing data, in this case quarterly. Those gathered polynomials share the same slope and curvature at the joining points. Those estimation need to follow different constraints. Here below follows the definition by Ajao, Ibraheem and Ayoola (2012):

Given a function $\boldsymbol{f}$ defined on $[\boldsymbol{a}, \boldsymbol{b}]$ and a set of numbers, called notes, points $(\boldsymbol{x_i}, \boldsymbol{y_i})$; $\boldsymbol{i = 0, 1, 2 \dots n}$, where $\boldsymbol{a < x_0 < x_1 < x_2 \dots < x_n = b}$, a cubic spline interpolant $\boldsymbol{S}$, for $\boldsymbol{f}$ is a function that satisfies the following conditions:

(a) $\boldsymbol{S}$ is a cubic polynomial, denoted $\boldsymbol{S_i}$ on the subinterval $[\boldsymbol{x_i}, \boldsymbol{x_{i+1}}]$ for $\boldsymbol{i = 0, 1, 2, \dots, n-1}$.

(b) $\boldsymbol{S(x_i) = f(x_i) = y_i}$; $\boldsymbol{for\ each\ i = 0, 1, 2, \dots, n}$

(c) $\boldsymbol{S_{i+1}(x_{i+1}) = S_i(x_{i+1})}$; $\boldsymbol{for\ each\ i = 0, 1,} 2, \boldsymbol{\dots, n-2}$

(d) $\boldsymbol{S'_{i+1}(x_{i+1}) = S'_i(x_{i+1})}$; $\boldsymbol{for\ each\ i = 0, 1, 2, \dots, n-2}$

(e) $\boldsymbol{S''_{i+1}(x_{i+1}) = S''_i(x_{i+1})}$; $\boldsymbol{for\ each\ i = 0, 1, 2, \dots, n-2}$

(f) One of the following boundary conditions is satisfied:

(i) $\boldsymbol{S''(x_0) = S''(x_n)}$; $(\boldsymbol{free\ or\ natural\ boundary})$

(ii)

$\boldsymbol{S'(x_0) = f'(x_0) = y_0\ and\ S'(x_n) = f'(x_n) =}$
$\boldsymbol{y_n}$; $(\boldsymbol{clamped\ boundary})$.

Applying this methodology through Matlab enables to get monthly data for all our explaining variables and thus to handle them properly.

b. Cointegration tests

Before analysing the link between stock-bond correlation and the economic factors given above, the cointegration of those factors with the stock-bond return relation needs to be tested. Testing cointegration is indeed crucial since it indicates whether your

explaining variables have a meaningful long-run relation with the explained variable. If no cointegration is found between variables, it means that those have different trend processes and that inference might be biased.
To test cointegration between stock-bond correlation and the picked variables, we use the Engle and Granger test (1987). As a matter of fact, among the cointegration tests available in Matlab, the latter seems to be more suitable given that the Johansen test (1995) relies on asymptotic properties that can lead to misspecification errors in limited samples, which is the case here.

The Engle-Granger test is divided in two steps. During the first one, the co-integrating regression is estimated:

$$\boldsymbol{x_{1,t} = \beta_1 + \beta_2 x_{2,t} + \cdots + \beta_p x_{p,t} + u_t}$$

with $\boldsymbol{p}$ the number of variables.

If there is cointegration among the variables, the residuals $\boldsymbol{u_t}$ will feature stationarity, which means there is a long-term meaningful relationship.

The second step is to test the stationarity of the residuals using and Augmented Dickey Fuller test as previously explained in section 3.c.i. The null hypothesis suggests no cointegration while the alternative one indicates the presence of cointegration among the variables.
We find the following results in Europe and in the United States:

P-value	INF	EXPINF	GDP	VOL	INT
EU	0,001	0,001	0,0018	0,001	0,001
US	0,0084	0,0078	0,0089	0,0015	0,0036

Table 5.1 Engle-Granger test p-values

As can be noticed, the p-values are below the confidence level of 5% suggesting that the null hypothesis of no cointegration should be rejected for each variable in Europe and in the United States. In other words, those results show that there is a long-term relation between each one of those factors and the stock-bond correlation.

c. Model and methodology

In order to assess the link between stock-bond correlation and the previously enumerated economic factors, the multiple linear regression technique is to be used. As shown in Li (2002), this method presents indeed the advantages of easiness of understanding and satisfying results. Accordingly, the following formulation is applied in Europe and in the United States:

$$\boldsymbol{Corr_t = \beta_0 + \beta_1 INF_t + \beta_2 EXPINF_t + \beta_3 GDP_t + \beta_4 VOL_t + \beta_5 INT_t + \varepsilon_t}$$

Starting from this regression, we first analyse the correlation coefficients between the variables to avoid collinearity issues among the model. Following this step, we take the differentiated form of one of the two highly correlated variables. Afterwards, we add and withdraw one at a time all the variables in order to see whether they are all significant. In the end, among the significant models, we use the criteria of the highest R-squared to pick the model that best fits the data.

Another way of analysing the relation between the different explaining variables and stock-bond correlation would have been to develop a simple linear regression for each. However, those models are run in order to analyse the way stock-bond correlation is influenced by different economical factors. Therefore, we will try to keep a maximum of significant variables whenever possible. Furthermore, we need to maximize the R-squared since the most efficient combination of variables will be used to forecast stock-bond correlation in the next section and a single linear regression will not lead to high R-squared levels.

d. Results

i. Europe

In Europe, the following correlations among the variables are obtained:

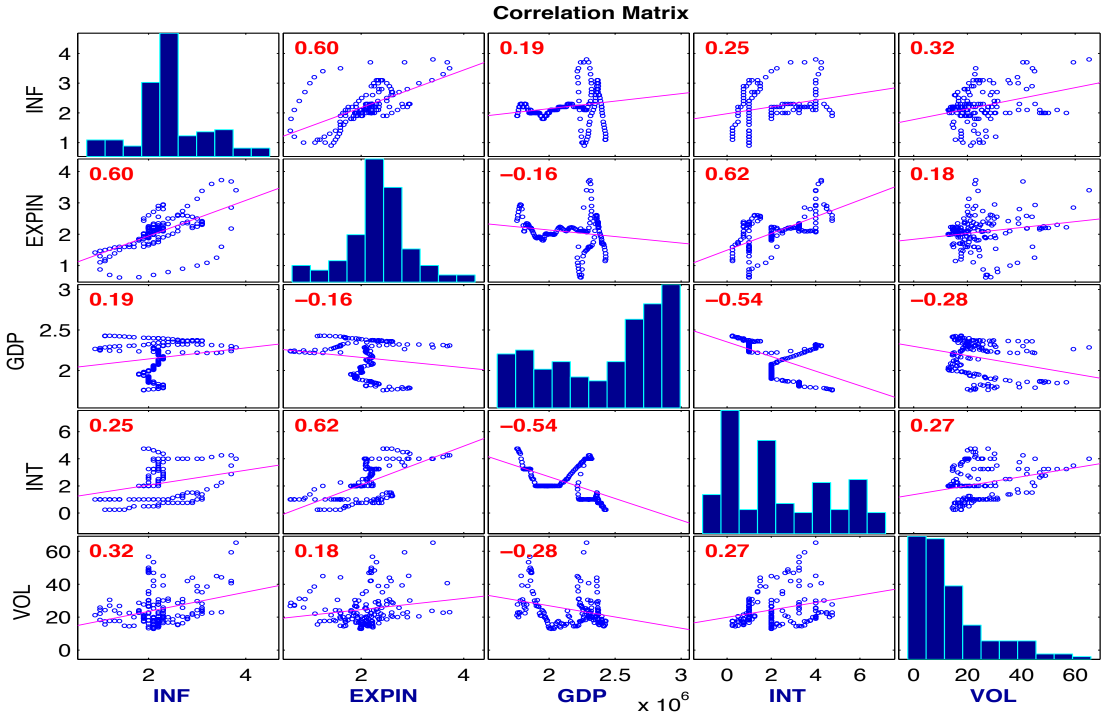

Figure 5.1 Correlation coefficients among EU variables

The red number gives the correlation coefficient between variables and its colour suggests that it is significantly different than 0.

We notice that the variable expected inflation seems to be highly correlated with inflation and interest rates. That's why we opt for the differentiated of it for the rest of our analysis. The model with the 5 regressors still does not seem significant. With 4 regressors, we also fail to find a significant formula. In the end, we believe that the model regressing stock-bond correlation with the GDP growth, differentiated expected inflation and implied volatility of stock option indexes is significant with an R-squared of 0,362. We find here below the results:

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.41544	0.13666	3.0399	0.0027759
x1	-2.4535e-07	5.7213e-08	-4.2884	3.1426e-05
x2	-0.011781	0.0012777	-9.2207	1.947e-16
x3	-0.31323	0.10254	-3.0546	0.0026507

Number of observations: 160, Error degrees of freedom: 156
Root Mean Squared Error: 0.145
R-squared: 0.362, Adjusted R-Squared 0.349
F-statistic vs. constant model: 29.5, p-value = 3.78e-15

Table 5.2 Results of the EU multiple linear regression

with x1 the GDP growth, x2 the implied volatility and x3 the differentiated expected inflation.

As we observe that the intercept takes a large value, we might think that this will lead to analysis errors. However, when withdrawn, the other coefficients keep values close to the ones found here, for a lower R-squared. The coefficients found all feature a negative relation with stock-bond comovements. Those results are in agreement with what was expected about the uncertainty measures and to some extent, the economic growth, as found in Europe by Perego and Vermeulen (2013). Surprisingly however, the changes in expected inflation feature a negative relation with the stock-bond correlation. Subsequently and in order to seek an explanation of the sign of this regressor, we develop a chart comparing the correlation coefficient and the differentiated expected inflation in Europe:

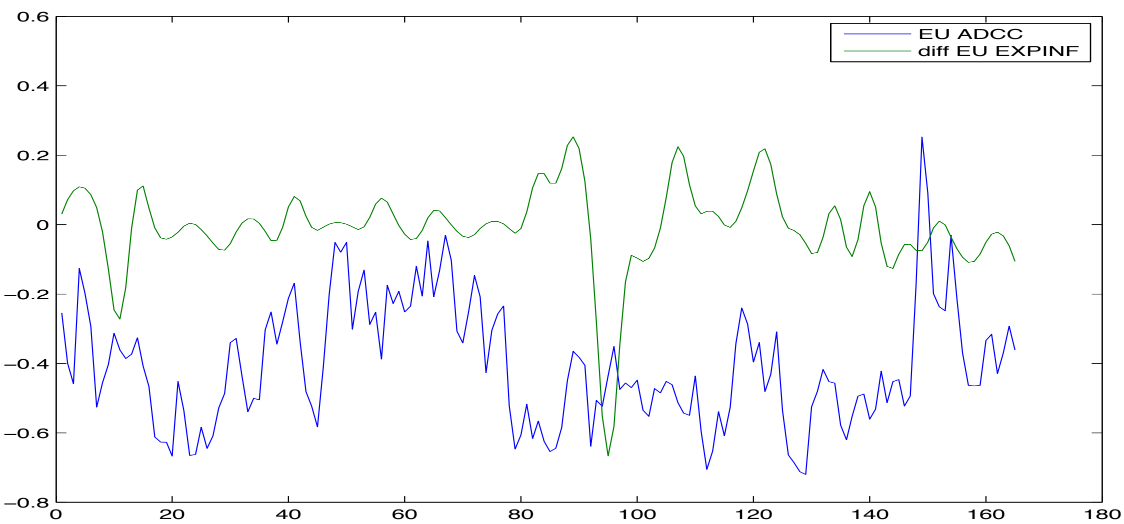

Figure 5.2 Comparison of EU ADCC with expected inflation

It is difficult to establish a clear trend, as on appearance, those two variables do not seem really related to each other. In that light, we conclude that no finite conclusion should be drawn about the existing link between expected inflation and stock-bond return comovements in Europe.

ii. United States

The same process is applied to the United States financial markets. Firstly, correlation coefficients among the variables must be analysed so as to avoid collinearity:

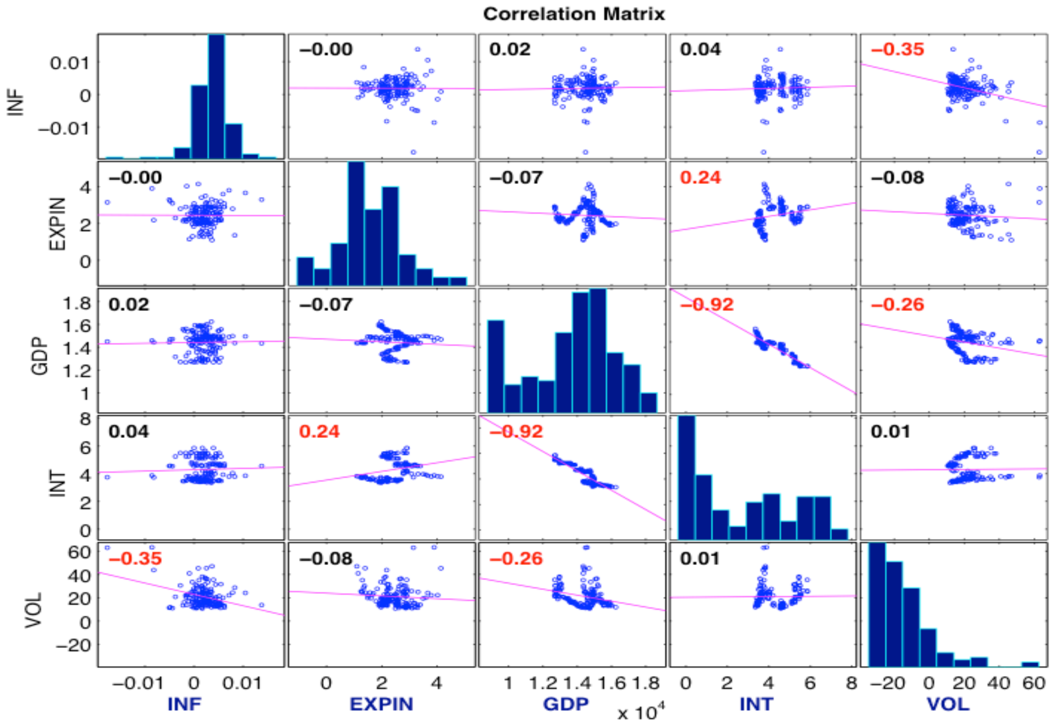

Figure 5.3 Correlation coefficients among US variables

We notice in the above table the large absolute value of correlation coefficient between the interest rate and the GDP growth. We test then combinations by taking the differentiated value of those factors. In the end, we strive to find a satisfactory combination of explanatory variables that are significant and produce decent explanation power. We find that the two major drivers are the implied volatility of stock options index and the GDP growth. But we see that adding the interest rate variable enables to improve the explanation power of the regression. That's why we decide to also keep this factor despite the clear inverse link with GDP growth. We find here below the results:

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-3.3547	0.96627	-3.4719	0.00066887
x1	0.0001414	4.8735e-05	2.9014	0.004252
x2	-0.0046717	0.0019509	-2.3946	0.017826
x3	0.25238	0.057032	4.4253	1.8003e-05

Number of observations: 160, Error degrees of freedom: 156
Root Mean Squared Error: 0.171
R-squared: 0.3, Adjusted R-Squared 0.286
F-statistic vs. constant model: 22.2, p-value = 4.78e-12

Table 5.3 Results of the US multiple linear regression

with x1 the GDP growth, x2 the implied volatility and x3 the interest rate.

As in Europe, we compare the obtained results with the ones without an intercept and find that the regression coefficients suffer only minor changes but that the R-squared diminishes significantly. The signs of the coefficients are more in line with what would the previous literature suggest than in Europe. Indeed, the GDP growth features a positive relation with the stock-bond correlation, as it has been previously found in the United States. The implied volatility, representing the uncertainty of the investors shows an expected negative sign. And finally, the interest rate is positively related to the stock-bond returns comovements as it impacts equally both markets.

iii. Conclusion

We can conclude that the implied volatility, reflecting an uncertainty measure, has played an essential role in the low correlation coefficient experienced in Europe and the United States. The growing lack of confidence of the investors in the financial markets has driven the stock-bond return relation down. It is more difficult to draw conclusions from the mixed results regarding the GDP growth. While the expected inflation does not deliver a clear understanding of its link with the correlation coefficient in Europe, the way interest rates in the United States impacted SBC seems more explicit. The gradual decline of interest rates leads to a lowering of correlation.

6. Forecasting

This section of the study is an important step toward the possibilities of application of stock-bond correlation. It is also a parsimonious one since a technique enabling to forecast accurately the events that are going to occur is going to happen in financial markets does not properly exist.

We will first develop the technique to forecast the stock-bond returns relation and assess the results, and then the same framework will be applied to the assets volatility.

a. Forecasting the SBC

To forecast the stock-bond correlation, we have decided to apply a method presented in Fair and Shiller (1990). Thoroughly familiar with this approach, it has also proved to be, while not overly complex, highly efficient. Basically, we run linear correlations between the correlation coefficient one month outside the rolling window and the explaining factors inside the rolling window. The given explaining factors are the ones that were found relevant in the previous section. To choose the size of the rolling window, various tests have to be carried, namely confusion matrixes, mean absolute percentage error and statistical significance of the model. The size of the rolling window will be between two and six years in order to have enough observations on one hand, and not to take a too high proportion of the data on the other hand.

i. Confusion matrixes

The test of the confusion matrix is the first one to be run. Its intent is to inform of how accurately forecasts give the direction of changes of the forecasted value (Swanson and White, 1997). However, it does not provide any information about how close the forecasts are to the actual value nor the precision of the change size.

To apply it, we start by comparing the direction of changes given by the forecasts to the actual ones. A 2 by 2 matrix is constructed filled with the number of successful and unsuccessful forecasts both in the up and down sides with the correct ones on the diagonal. The final step of the tests takes the form of an independency test on a contingency table with as null hypothesis the independency of column and row variables. Hence, we first compute the expected frequencies by applying:

$$\boldsymbol{E_{i,j}} = \frac{\boldsymbol{O_{i\cdot}O_{j\cdot}}}{\boldsymbol{N}}$$

with $\boldsymbol{O_{i\cdot}}$ the sum of observations of row $\boldsymbol{i}$ and $\boldsymbol{N}$ the total number of observations.

Then we calculate the test-statistic:

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{\left(\boldsymbol{O_{i,j}} - \boldsymbol{E_{i,j}}\right)^2}{\boldsymbol{E_{i,j}}}$$

This test-statistic follows a Xhi-square distribution with $(\boldsymbol{r}-\mathbf{1})(\boldsymbol{c}-\mathbf{1}) = 1$ degree of freedom. We find here below the results with the p-values:

EU independence tests	2-year	3-year	4-year	5-year	6-year
Test-statistic	0,9162	0,9759	4,6963	1,8199	2,0428
P-value	< 0,00001	< 0,00001	< 0,00001	< 0,00001	< 0,00001

Table 6.1 EU confusion tests

US independence tests	2-year	3-year	4-year	5-year	6-year
Test-statistic	1,1271	0,2359	0,0665	2,2642	3,2401
P-value	< 0,00001	< 0,00001	< 0,00001	< 0,00001	< 0,00001

Table 6.2 US confusion tests

As we can observe, the null hypothesis is rejected in each case with a very high confidence level, suggesting there is dependence between the predicted change directions and the actual ones.

ii. Mean absolute percentage error

The second decision instrument that we use is the mean absolute percentage error. As stated by its name, it gives the average absolute error in percentage of the forecasts in the estimation process of the data. The best prediction model will be the one whose mean absolute percentage error is the lowest.

Its formula is given by Stekler (1991):

$$\frac{\sum_{t=1}^{T} \frac{|forecast_t - data_t|}{|data_t|}}{T}$$

The results are the following:

	2-year	3-year	4-year	5-year	6-year
MAPE EU	0,7621	0,725	0,702	0,5805	0,5175

Table 6.3 MAPE EU

	2-year	3-year	4-year	5-year	6-year
MAPE US	2,0541	1,5207	1,0207	1,1038	1,066

Table 6.4 MAPE US

While the results do not suggest a good fit of the model especially in the United States, we can identify the 6-year rolling window as the most efficient one.

iii. Statistical significance of the model

We first test the significance of the model compared to the constant one thanks to an F-statistic. The results are unanimous as the constant model is rejected in each of the 10 models.

To push further the analysis, we compare the average statistical significance of each explaining factor in each length of rolling window:

Coefficients EU	Constant	GDP growth	Implied Volatility	Diff exp inflation	R-squared
2-year	-0,5730	9,71E-08	-0,0079	0,0919	0,36
P-value	0,31	0,28	0,24	0,52	
3-year	-0,4727	1,04E-07	-0,0084	0,0737	0,35
P-value	0,26	0,26	0,15	0,47	
4-year	0,3026	-2,15E-07	-0,0096	-0,0430	0,38
P-value	0,25	0,23	0,02	0,45	
5-year	0,6830	-3,79E-07	-0,0096	-0,1724	0,39
P-value	0,21	0,18	0,00	0,22	
6-year	0,7424	-4,08E-07	-0,0099	-0,2983	0,40
P-value	0,14	0,14	0,00	0,16	

Table 6.5 EU statistical significance of the coefficients and R-squared

Clear improvements are observed both in the significance of the explaining factors and in the R-squared as we extend the length of the observation window. This suggests that the 6-year rolling window delivers a better fit for forecasts.

Coefficients US	Constant	GDP growth	Implied Volatility	Diff exp inflation	R-squared
2-year	-1,0247	-2,85E-05	-0,0029	0,2659	0,35
P-value	0,25	0,25	0,34	0,37	
3-year	-0,1922	-4,23E-05	-0,0049	0,1183	0,34
P-value	0,17	0,17	0,29	0,21	
4-year	-0,3668	-5,00E-05	-0,0074	0,2140	0,38
P-value	0,17	0,17	0,18	0,26	
5-year	-0,7360	-4,35E-05	-0,0075	0,2906	0,39
P-value	0,14	0,15	0,20	0,13	
6-year	-0,8542	-2,73E-05	-0,0061	0,2532	0,40
P-value	0,21	0,20	0,25	0,10	

Table 6.6 US statistical significance of the coefficients and R-squared

The results in the United States are less straightforward since the p-values indicate that the 5-year rolling window is a better fit while the R-squared supports the idea that the 6-year observation window explains better the forecasts.

Based on our decision criteria's, the 6-year rolling window seems to deliver the best forecasting performance in Europe and in the United States. However, the results are not satisfying, as the mean absolute percentage error has shown. This is the reason why we decide to add an autoregressive component to help improve the global forecasting performance of the model. Hence, we develop an ARIMAX (D,P,Q) model, which is the Autoregressive Integrated Moving Average with exogenous variables methodology. The difference with the previously explained ARMA (P,Q) model (see section 3.b.i.) is the presence of exogenous variables and a differencing factor. Precisely, the independent explaining variables that we use are again the ones we selected in section 5.d.i. and 5.d.ii. and we use a 6-year rolling window as it showed to be the most efficient. Although rolling windows may lead to highly volatile results (see there section 1.a.i.), the introduction of an autoregressive factor should result in smoother transmissions between sharp changes. In an attempt to keep our model as simple possible in order to avoid overfitting issues, we first only add the autoregressive part of the model to the exogenous variables. If those aren't efficient enough, we will progressively add other autoregressive and moving average coefficients. In our case, the ARIMAX (1,0,0) model has the following formula:

$$y_t = \alpha_1 y_{t-1} + \beta_1 x_{t-1}$$

with y the response variable and x the exogenous data.

Stationarity is a requirement in order to ensure adequate estimation; hence we apply the methodology of Leybourne-McCabe (Leybourne-McCabe, 1994) to check whether we need to difference the time series before modelling the ARIMAX (P,D,Q). The null hypothesis stands for an AR(p) process while its alternative suggests ARIMA(p,1,1) model. The test fails at rejecting the null hypothesis with a 0,10 p-value in both cases. We develop the forecasts and get the following results graphically:

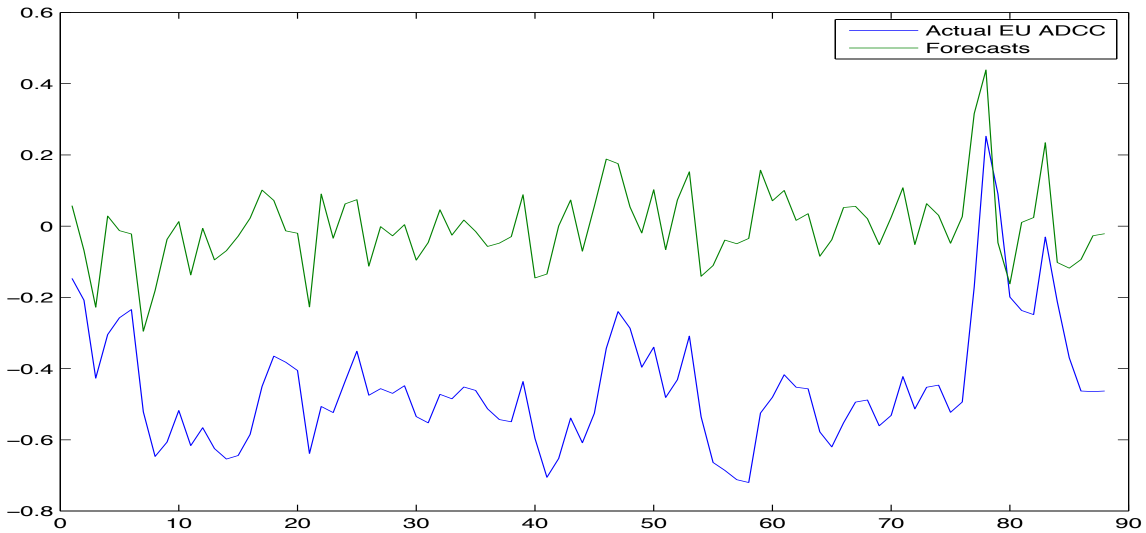

Figure 6.1 Comparison of EU ADCC forecasts with actual data

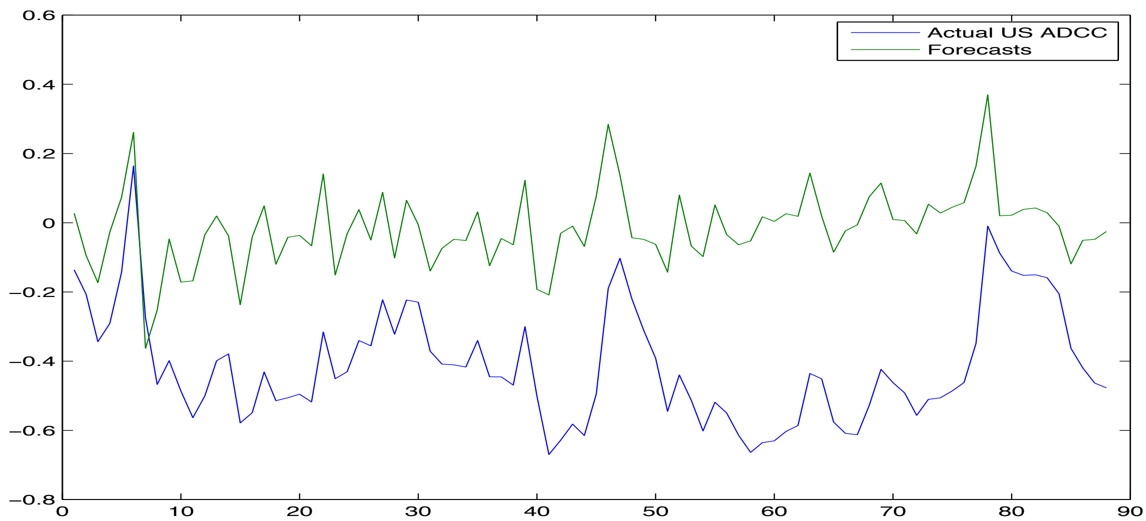

Figure 6.2 Comparison of US ADCC forecasts with actual data

The forecasts exhibit the same patterns as the real data. However, they are centred around 0 while the real correlation coefficient navigates largely in the negative values. It is probably explained by the fact that the time series is not adequately stationary. This issue can be fixed by retrieving the mean bia from the forecasts (Lawrence and Klimberg, 2011). While this observation is made after the observation window, we calculate the mean bia only with data from the past at each point in time in order to avoid chronological incoherencies. Applying this fix enables the method to be used in the future with high accuracy. Concretely, each forecast is reduced by the mean of previous errors. Graphically, we get the following:

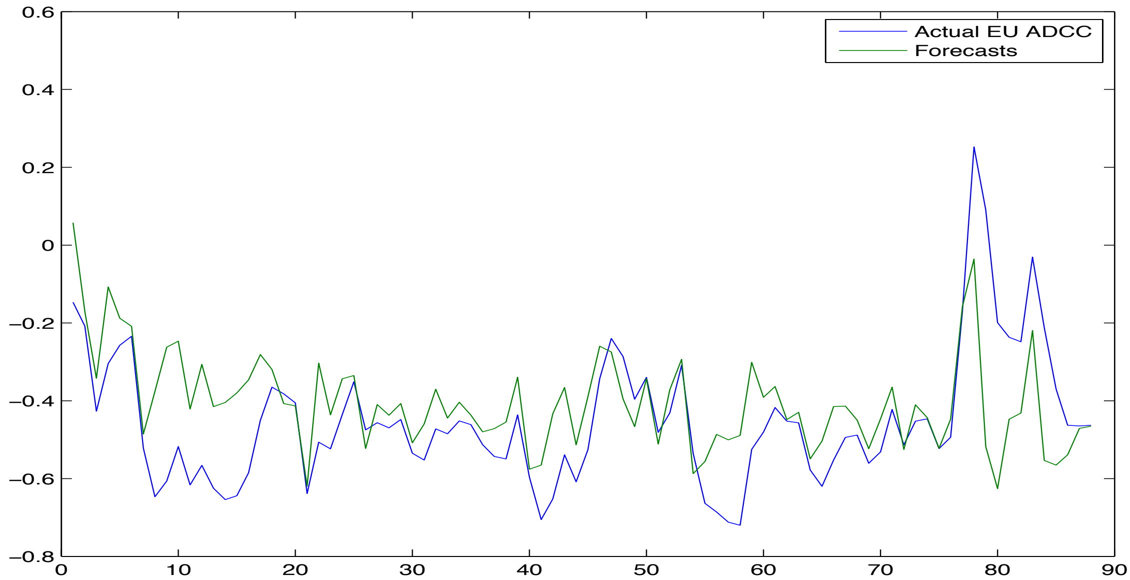

Figure 6.3 EU ADCC forecasts with correction of the mean bia

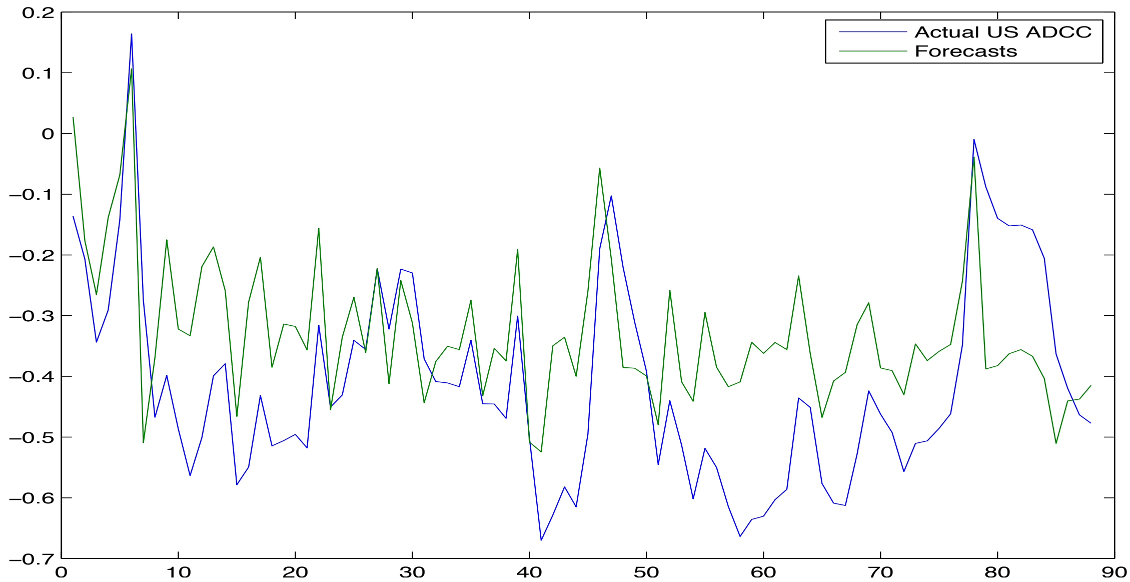

Figure 6.4 US ADCC forecasts with correction of the mean bia

And we get the following average coefficients of the model:

EU ADCC Forecast	Constant	Alpha	Beta
Coefficients	0,1945	0,7148	-1,38E-07

Table 6.7 EU ADCC forecasts coefficients

US ADCC Forecast	Constant	Alpha	Beta
Coefficients	0,5873	0,7287	-4,56E-05

Table 6.8 US ADCC forecasts coefficients

The MAPE are highly improved as shown below:

ADCC Forecasts	EU	US
MAPE	0,4063	0,4474

Table 6.9 ADCC forecasts MAPEs

We also make the test of independency between the forecasts and the actual data:

Independence tests	EU	US
Test-statistic	22,3116	30,625
P-value	< 0,00001	< 0,00001

Table 6.10 Confusion tests for the improved forecasts

The MAPEs are highly improved and that the hypothesis of independency between the forecasts change directions and the ones of actual data is rejected.

Considering the fact that our projection window corresponds to low negative values, it might lead to more accurate results to apply a rolling window for the computation of the mean bia correction if applied to an environment with widely varying correlation coefficients.

For further improvements, the technique developed by Engle and Sheppard (2001) could be followed. This methodology leads to forecasts of the correlation coefficient by dividing the forecasts of the covariance matrix by the ones of the assets volatility.

b. Forecasting the assets volatility

To forecast the volatility of the stock and bond markets in Europe and in the United States, we apply the technique of Monte Carlo simulation. The tool is provided in Econometrics Toolbox of Matlab and simulates sample paths of conditional variances based on the characteristics of the given time series volatility. Then, the average of the sample paths is computed at each point of time to get the forecasts.

More precisely, the first step is about estimating a volatility model for each month of forecasts. Matlab does not enable users to simulate TARCH processes. However, simulations of GJR-GARCH model is available, which is the one we select for Europe as that kind of volatility model performed quite well in the previous estimation (see section 3.c.iii.) and is close to TARCH one. Afterwards, we fit GJR-GARCH (1,1,1) for each date. For the United States market, we apply a GARCH (1,1) process, as it is the one previously recommended. The second step consists in the simulation of paths with the parameters of the models previously estimated. Each month, we simulate 500 paths of the length of the month. Finally, we take the average of those paths to create the monthly forecasts.

Here below, we find the results graphically for the equities in Europe:

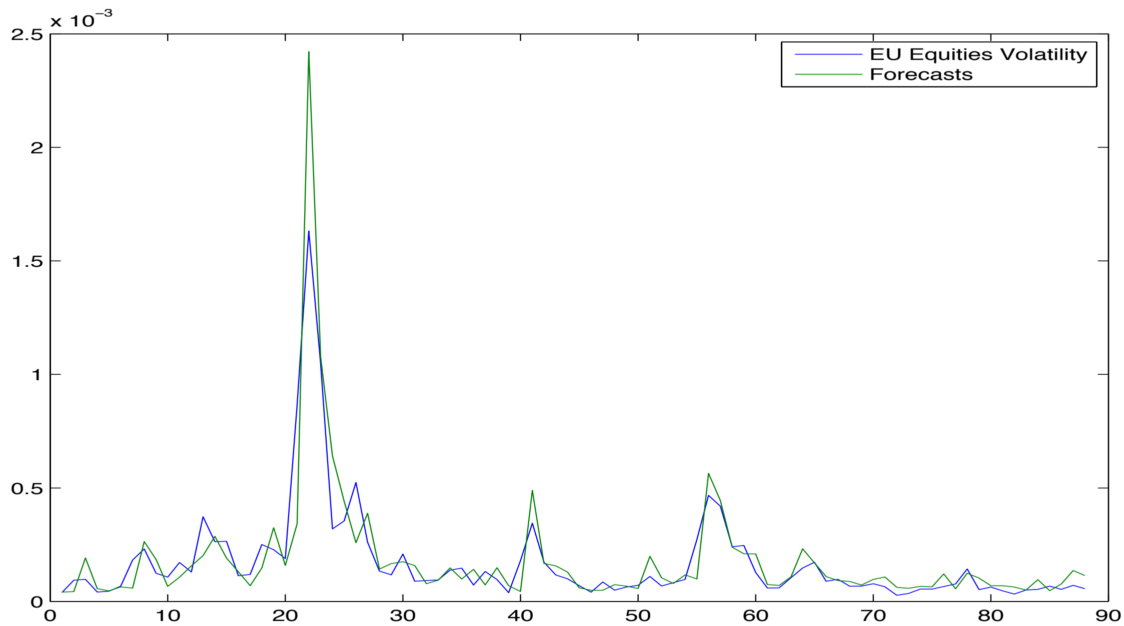

Figure 6.5 EU equities volatility forecasts

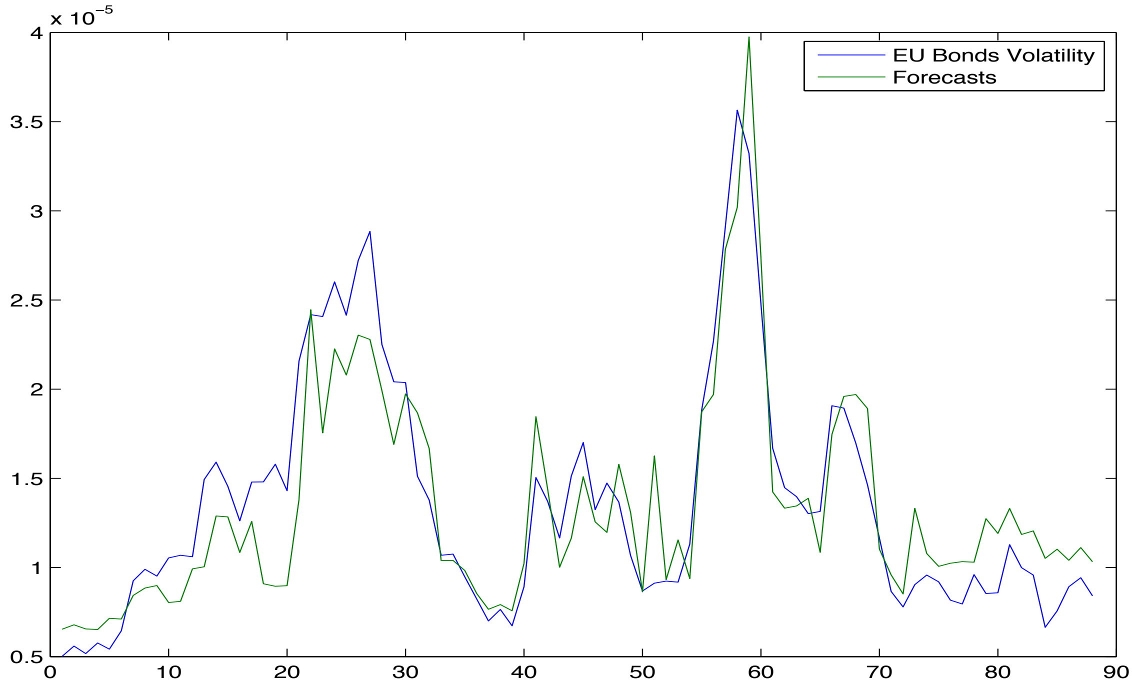

Figure 6.6 EU bonds volatility forecasts

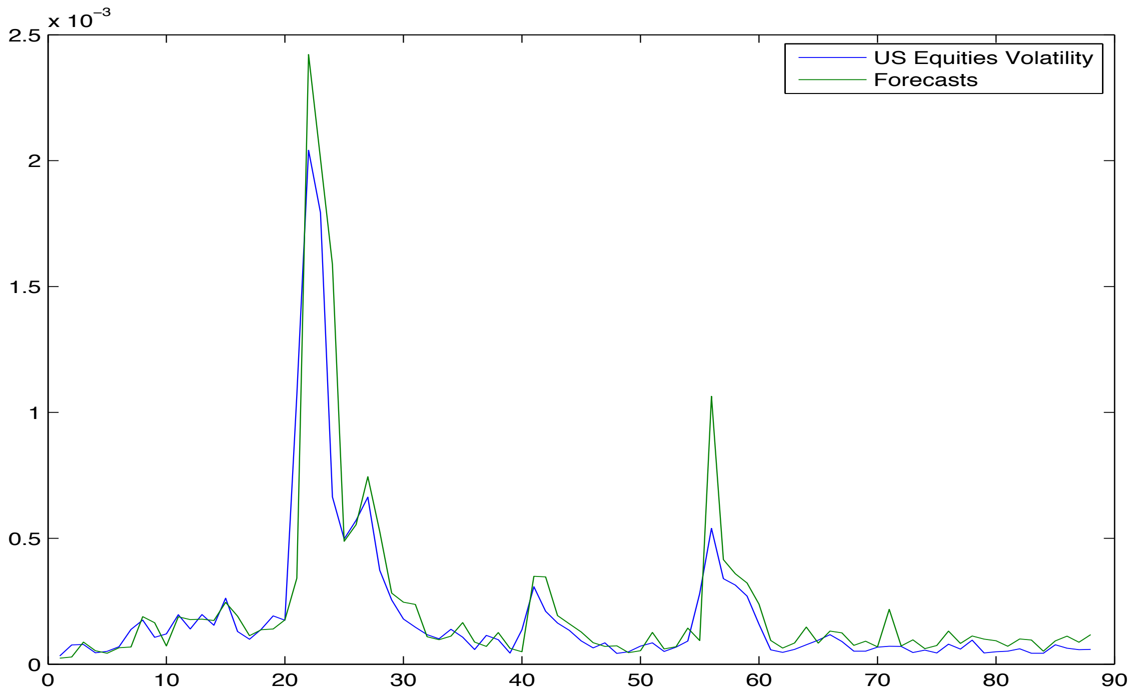

Figure 6.7 US equities volatility forecasts

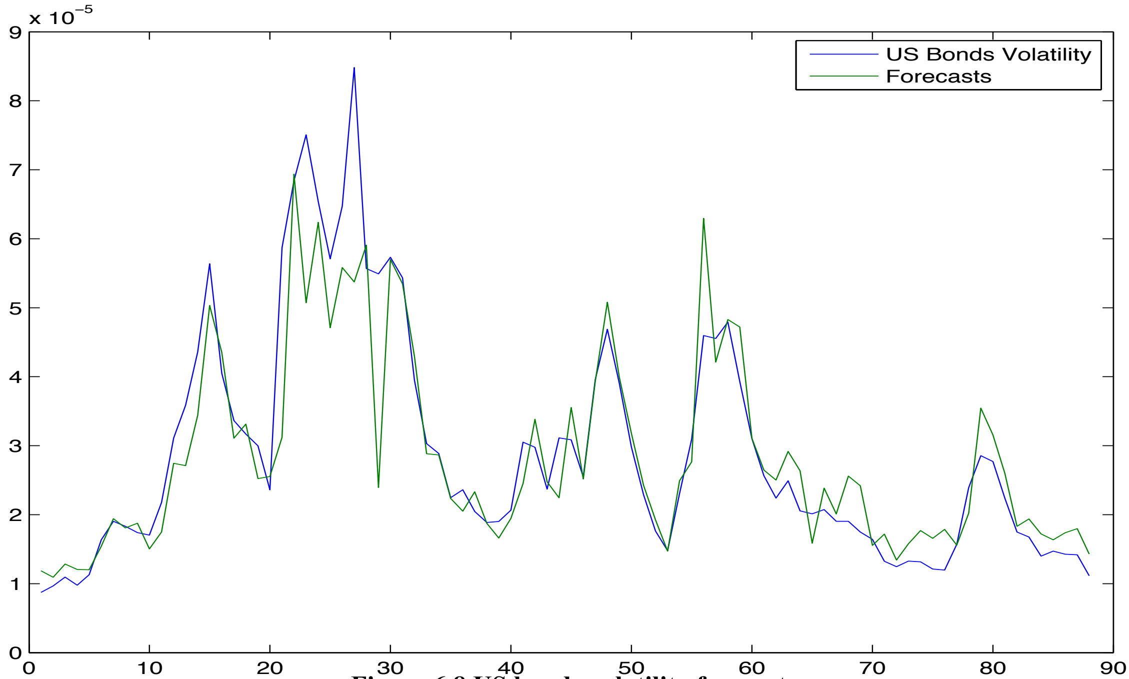

Figure 6.8 US bonds volatility forecasts

Globally, the results seem quite satisfying. It can additionally be noticed that the forecasts tend to be more volatile than the actual data. We compute the Mean Average Percentage Error to check the accuracy of the results:

MAPE	Stocks	Bonds
EU	0,3819	0,1801
US	0,3444	0,1431

Table 6.11 MAPE of the assets volatility forecasts

The results seem satisfying, especially in the bond markets which do the charts above confirm once we take the scale difference into account.

7. Value-at-Risk Optimization

This section will be devoted to show a way to reduce the risk exposure of a portfolio by using stock-bond correlation to indicate diversification opportunities.

a. Insight about Value-at-Risk and Conditional Value-at-Risk

Value-at-Risk (VaR) is defined as “the loss that would be exceeded with a given probability over a specific time period” (Chance, 2003). Chance (2003) insists that the VaR is a minimum loss and not what one should expect to lose at a given probability. Despite many critics, VaR has become arguably the most used standard risk measure. In enterprise risk management, VaR is perceived as “the amount of capital required to ensure, with a high degree of certainty, that the enterprise doesn’t become technically insolvent” (Klugman, Panjer and Willmot, 2012). The degree of certainty chosen is often 95%, or higher figures such as 99,5% in enterprise risk management.

Statistically, VaR is considered as the percentile (confidence level) of the distribution of the losses. In the case of continuous distributions, we mathematically define $\boldsymbol{VaR_p(X)}$ of the losses X as the value $\boldsymbol{\pi_p}$ satisfying (Klugman, Panjer and Wilmott, 2012):

$$\boldsymbol{Pr(X > \pi_p) = 1 - p}$$

However, VaR does not satisfy one of the four requirements for coherence - the subadditivity criterion (a portfolio with multiple assets can have a VaR higher than the sum of the individual VaRs) – in the case of distributions different from normal (Krokhmal, Palmquist and Uryasev, 2001). This problem arises often since assets returns feature skewness most of the time. Another issue encountered when dealing with VaR is the lack of information given when the threshold is exceeded, as we do not have any information about the importance of the losses above the VaR.

That is partly why new risk management measures have been created to improve and resolve the concerns encountered with VaR. One of them is Conditional Value-at-Risk (CVaR). CVaR satisfies the subadditivity requirement and gives hindsight about the losses exceeding the threshold. It has been given different names such as Mean Excess Loss, Expected Shortfall and Tail Value-at-Risk. It is basically the mean of all the losses exceeding the VaR threshold. It is then larger than VaR by that amount precisely. CVaR presents the advantage of being convex (Rockafellar and Uryasev, 2000), which facilitates its estimation. Klugman, Panjer and Wilmott (2012) define it as the "expected loss given that the loss exceeds the 100p percentile of the distribution of X" and give the following formulas:

$$\boldsymbol{CVaR_p(X) = E\left(X \middle| X > \pi_p\right)}$$
$$= \boldsymbol{\pi_p} + \frac{\int_{x_p}^{\infty} \boldsymbol{\left(x - \pi_p\right) f(x) dx}}{\boldsymbol{1 - p}}$$
$$= \boldsymbol{VaR_p(X)} + e\left(\boldsymbol{\pi_p}\right)$$

with $\boldsymbol{e\left(\pi_p\right)}$ the mean excess loss function at 100$\boldsymbol{p}$th percentile.

b. Model

We aim at reducing the risk exposure of a portfolio by minimizing its future VaR and to a lesser extent its CVaR. As the method to optimize CVaR [3] is beyond the scope of this study, our developments will be focused on the optimization of the VaR of a portfolio. The distribution of the returns is here very important as when the loss distribution is normal, the two kind of optimization lead to the same optimal weights (Rockafellar and Uryasev, 2000). Hence, while the returns distribution does not follow a normal distribution, we can reasonably presume that a VaR optimization will result in a portfolio with a CVaR close to optimal as well. However, if data are highly skewed, weights can be quite different and minimizing the VaR can stretch the tail exceeding the threshold (Larsen et al., 2002). To ensure we avoid this precise situation, we will ascertain the skewness of the returns once the optimal weights have been estimated.

As the returns distribution does not prove to be normal in both regions, we use the 95% percentile of the student distribution.

[3] See Rockafellar and Uryasev, 2000. As there is not a proper method to minimize a conditional value, they derive a new function from the CVaR formula and apply the optimization on the former, which leads to an optimal solution applicable to the latter.

The optimization problem is then the following:

$$\boldsymbol{min}\ \mathbf{1,662} * (\boldsymbol{x_s^2} * \boldsymbol{\sigma_s^2} + \boldsymbol{x_b^2} * \boldsymbol{\sigma_b^2} + \boldsymbol{x_s x_b} * \boldsymbol{\rho_{sb}} * \boldsymbol{\sigma_s} * \boldsymbol{\sigma_b})$$

$$\text{s. t.}\quad \boldsymbol{a} < \boldsymbol{x_s} < \boldsymbol{c}$$

$$\boldsymbol{a} < \boldsymbol{x_b} < \boldsymbol{c}$$

$$\boldsymbol{x_s} + \boldsymbol{x_b} = \mathbf{1}$$

where $\boldsymbol{x_{s,b}}$ is the weight of stocks/bonds, $\boldsymbol{\sigma_{s,b}}$ forecasts of the standard deviation of stocks/bonds, $\boldsymbol{\rho_{sb}}$ forecast of the stock-bond correlation, a the lower-bound of the weights and c the upper-bound of the weights.

The optimal weights are estimated using the forecasts of correlation and volatilities and then applied to the actual data in order to measure the success of such a strategy.

c. Results

To assess the performance of this strategy, we compare the results to the one of an equally weighted portfolio, 50% in the stock market and 50% in the bond market. As a reminder, the goal of this strategy is not to improve profitability but to manage the risk of a portfolio. The purpose being the reduction of the risk exposure of the investments made, we will compare the VaRs generated by the two investment modes. However, as stated before, VaR does not provide any insight about what occurs when its threshold is exceeded. That is why it is important to also monitor the amount of losses when the VaR threshold is crossed. In order to do so, we also compare the resulting CVaRs:

EU Optimization	Avg stocks weight	Opt VaR	EW VaR	Paired t-test	P-value	Opt CVaR	EW CVaR
> 10% bound	17,27%	0,0054	0,0105	10,838	< 0,00001	0,0135	0,0343
> 20% bound	22,88%	0,0058		12,0128	< 0,00001	0,0164	
> 30% bound	31,00%	0,007		13,4738	< 0,00001	0,0183	
> 40% bound	40,84%	0,0087		13,8986	< 0,00001	0,0263	

Table 7.1 EU VaR optimization results

US Optimization	Avg stocks weight	Opt VaR	EW VaR	Paired t-test	P-value	Opt CVaR	EW CVaR
> 10% bound	23,92%	0,0075	0,0115	7,1584	< 0,00001	0,0218	0,032
> 20% bound	26,73%	0,0077		7,8666	< 0,00001	0,0226	
> 30% bound	32,91%	0,0084		9,0174	< 0,00001	0,0225	
> 40% bound	41,39%	0,0098		9,9144	< 0,00001	0,0276	

Table 7.1 US VaR optimization results

The results indicate at a high level of confidence that the strategy leads to a lower risk exposure than an equally weighted portfolio would. In order to demonstrate that our results are consistent and are not only a consequence of a higher proportion amount invested in the less volatile asset, the minimum weights allocated to one asset are varied. The weights are indeed fairly different depending on the time. Paired t-tests are then used in order to show that the difference in VaR is significant, as our return distribution does not follow a normal and the observations are paired. As those tests have been used in Amenc et al. (2012), it can be concluded that they are useful and reliable in similar studies as ours. The differences in CVaR also look significant although the paired t-test methodology cannot be applied to this kind of data to prove so. The skewness of the data (-0,28 in Europe and -0,31 in the United States) is low and CVaRs are improved, hence minimizing VaR did not lead to stretching the tail.

Conclusion

This thesis investigated stock-bond correlation in Europe and the United States in order to determine, on one hand, the reasons of its low level since the start of the 21st century and, on the other hand, to reduce the risk exposure of a two-assets portfolio.

After having examined the existing literature on the subject and in order to analyse the previously exposed issues, we develop the Asymmetric Dynamic Conditional Correlation model of Engle (2004). This model takes into account the asymmetric effects of volatility and conditional covariance, and avoids the issues linked to relying on rolling window (Engle, 2002). From January 2001 to October 2014, the obtained results indicate average stock-bond correlations in Europe and the United States of -0,41 and -0,33 respectively.

In an attempt to explain the low correlation coefficient, the evolution of the stock-bond return relation has been analysed through the financial shocks during the 2007-2009 global crisis and the Euro area sovereign debt crisis. In this context, we have noticed the appearance of numerous Flights-To-Quality following negative economic news. The major shocks that financial markets have endured during the 2007-2009 global financial crisis were satisfactorily absorbed by the government bond markets since the latters have not been declining as well. In financial turmoil, investors are necessarily willing to shift their stakes to what is perceived as a safe asset (Gulko, 2002). Government bonds, which were believed to be free of default risk, played that role quite efficiently during the Subprime crisis. Besides and as defined by a Flight-To-Quality (Baur and Lucey, 2008), the stock-bond correlation was negative and as investors were turning their back to plunging equities, they managed to land in a well-performing bond market.

The 2008 crisis leftovers and manipulated debt figures quickly led to the Euro area sovereign debt crisis. With the growing amount of countries in trouble to finance themselves, the assumption of absence of default risk in government bonds started to be challenged. Burgeoning concerns that some troubled countries might default led the bond market to enter in a sharp decline starting in mid-January 2010. Coupled to rising equities, it would look as a Flight-From-Quality, however the financial circumstances might suggest that investors have been looking for liquid assets. Consequently, the

German Bund became a very attractive opportunity and so were equities, suggesting the falling correlation coefficient was actually reflecting a Flight-To-Quality. On the time interval considered, no contagion episode seemed to take place, indicating that policymakers and regulators successfully supported financial stability (Das, 2003). These various flights encountered in financial turmoil finally resulted in a low stock-bond correlation environment in Europe and the United States.

Analysing the drivers of the stock-bond return relation and observing their evolution is another useful way to understand its level. Resulting from a multiple linear regression model, it emerged that the investors' sentiment possesses high explanation power regarding the correlation coefficient. The financial turmoil since 2008 has considerably lowered investors' confidence in a stable growth of financial market. This lack of trust negatively impacted stock-bond correlation as they quickly turn to safe diversification opportunities in case of bad news affecting financial markets. Conversely, interest rates positively contributed to the stock-bond return relation. The low interest rate environment experienced since 2008 has then lowered the correlation coefficient lately. Unfortunately, the mixed results obtained regarding GDP growth and expected inflation prevent us from drawing any conclusion regarding these economic variables.

The analysis previously achieved enables to successfully test whether stock-bond correlation can be applied in order to reduce the risk exposure of a portfolio.
Following the forecasts of the assets volatility and the correlation coefficient, the Value-at-Risk optimization, leading to close-to-optimal Conditional Value-at-Risk solutions (Rockafellar and Uryasev, 2000), proves to lead to significantly less risky portfolio than an equally weighted strategy would. So as to take our policy further, it would certainly be judicious to broaden the asset classes included in the optimization as to observe whether an even lower risk exposure could be attained. A focus should also indubitably be placed on this optimization during the worst shocks the studied financial markets have experienced up to now, in order to derive a strategy to be followed for the next presumable dramatic occurrences and therefore achieve to never lack of diversification opportunities.

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